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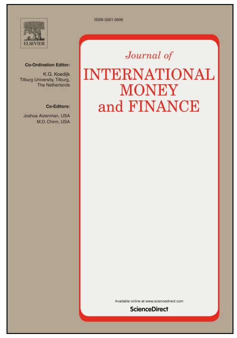

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Highlights

- We analyze the information content of sovereign CDS pricing errors
- A price discrepancy measure is estimated from the residuals of a non-arbitrage model
- This discrepancy measure reflects frictions such as illiquidity
- Exits of capital arbitrage in distress periods are linked to larger pricing errors
- Results are robust for the most common CDS pricing models

Market Frictions and the Pricing of Sovereign Credit Default Swaps

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Abstract

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Keywords: Credit default swaps, noise measure, illiquidity, capital arbitrage.
JEL classification: G01, G12, G15, G32

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1. Introduction

In this paper, we examine the economic determinants that underlie sovereign CDS pricing errors. The main aim is to ascertain systematic patterns in price divergences from a theoretical non-arbitrage term-structure CDS model stemming from market frictions, transaction costs, and local or global illiquidity conditions. The central hypothesis is that illiquidity-related factors cause declines in arbitrage activity and, hence, price deviations from fundamental values, as discussed by Merton (1987), Tuckman and Vila (1992), Schleifer and Vishny (1997), Brunnermeier and Pedersen (2009) and Duffie (2010), among others. As acknowledged in this literature, arbitrage is an inherently risky and costly activity due to market inefficiencies which makes arbitrageurs reluctant to trade when the cost of implementing their strategies is prohibitive. Similarly, the existence of capital constraints and/or capital rescissions, typically observed during market downturning scenarios, impose limits to the strength of arbitrage. As a result, the lack of sufficient arbitrage capital breaks the general agreement about pricing and enables assets to be traded in equilibrium at prices significantly different from their fundamental values. In this context, trading and holding costs as well as other market variables which are expected to have a strong influence on arbitrage capital could explain and even predict price divergences. The study of the role played by such illiquidity-related factors would be particularly insightful in markets which are usually characterized by intense professional arbitrage activity, such as the sovereign CDS market. Like other key aspects involved in the price formation process of these derivative contracts, however, little is formally known on this issue because active CDS trading is a relatively new phenomenon.

This paper strives to contribute to the extant literature and the general understanding on how CDS prices are formed by analyzing the informational content of pricing errors in the sovereign segment, characterizing when mispricing is more likely to occur, and pinpointing the main factors that drive and even predict fundamental-value divergences. To this end, we implement robust panel-data techniques –including two-way cluster errors, fixed-effect panel data, instrumental-variable (IV) and GMM-based panel data estimation– on a broad sample of weekly sovereign CDS spreads in 16 advanced and emerging economies in the period 2008 to 2012. In this analysis, contemporaneous (lagged) values of different illiquidity-related variables that capture transaction costs and proxy for changes in arbitrage capital at the individual level are used to explain (forecast) a suitable measure of CDS term-structure price divergence when controlling for a number of alternative factors.

The measure of price discrepancy, adapted from Hu et al. (2013), is defined as the logarithm of the average root mean square deviation between the market and a theoretical model-implied CDS term structure at a particular date. The main discussion follows for the analysis based on theoretical prices generated by the arbitrage-free default-intensity model in Pan and Singleton (2008). For the sake of robustness, however, we alternatively consider the spline-type model in Nelson and Siegel (1987) and the conditional default probability curve in Houweling and Vorst (2005), noting that the main results are not driven by the particular choice of the theoretical CDS term-structure pricing model.[1]

The main evidence from this analysis us to draw several conclusions. The most important result is that there exists a strong empirical connection between market-wide illiquidity factors and sovereign CDS missvaluation. In particular, larger bid-ask spreads (the most usual proxy for illiquidity and transaction costs in the extant literature) are systematically related to larger CDS pricing errors, both contemporaneously and in one-week ahead periods. Similarly, increments in the number of CDS offsetting transactions (a measure of effective trading activity) tend to increase pricing errors, mainly, in the segment of advanced economies. The general rationale for these general findings lies in the existence of a link that ties arbitrage activity to market illiquidity, as discussed previously. Consequently, the empirical evidence in this paper provides empirical support for the general suitability of the theoretical claims of the limit-to-arbitrage literature in the specific context of sovereign CDS markets.

In addition, this paper provides clear insight into the systematic patterns –both in the time-series and in the cross-section– that characterize mispricing in sovereign CDS markets. As expected under the arbitrage capital hypothesis, price deviations substantially increase during periods of financial distress such as Lehman's collapse in September 2008, or the Greek bailout in March 2010. Pricing errors are mostly contributed by divergences at the 1-year maturity, which could be related to limited cash vehicles with which to hedge such instrument, as discussed by Pan and Singleton (2008). Structural differences in cred-

[1] There exists several methods for pricing default swaps. On the one hand, a common practice in the industry is to bootstrap the survival probabilities from the observed quotes. To this end, both nonparametric (piecewise constant hazard rates) and parametric (Nelson and Siegel, 1987) interpolation methods are commonly used in practice. On the other hand, the intensity modeling approach has been extensively accepted among researches for pricing fixed income instruments such as corporate bonds (Lando (1998) or Duffie and Singleton, 1999) and default swaps (Longstaff, Mithal and Neis (2005), Pan and Singleton (2008) and Longstaff, Pan, Pedersen and Singleton, 2011).

itworthiness between advanced and emerging economies are also responsible of systematic differences in pricing errors in the cross-section. Furthermore, pricing errors exhibit sizable cross-country commonalities that suggest that systematic mispricing in the CDS market is (partially) driven by global trends. A simple principal component analysis reveals that about 50% of the total variation in pricing errors can be explained by two principal components. The projection of the first component on market-wide illiquidity- and volatility-related factors results in statistically significant coefficients and R^2 measures of about 26%, suggesting that this latent factor can be related to global market illiquidity. From a more sophisticated perspective, and as discussed previously, the panel-data analysis shows that the price divergences significantly covariate with market-wide illiquidity measures after controlling for other potential drivers, leading to R^2 measures of about 95%. These conclusions hold after controlling for a number of macroeconomic and financial state variables, using different estimation techniques, and different pricing models. The overall implication is that sovereign CDS prices must be driven by different risk factors which include, at least, a time-varying source of non-diversifiable illiquidity risk. This interpretation is consistent with the increasing evidence about the existence of an illiquidity component in credit markets in general, and CDS in particular.

This paper belongs to the stream of literature devoted to CDS pricing and illiquidity. A non-exhaustive review of this literature includes the papers by Longstaff et al. (2005), Tang and Yan (2008), Bongaerts, Jong and Driessen (2011), Nashikkar, Subrahmanyam and Mahanti (2011) or Corò, Dufour and Varotto (2013), among others. Earlier studies in this field argued that CDS prices may not be significantly affected by liquidity because their specific contractual nature makes it possible to easily trade large notional amounts compared to bond markets; see, for instance, Longstaff et al. (2005) and Blanco, Brennan and Marsh (2005). However, the recent literature largely supports the hypothesis that CDS prices are driven by a default risk factor and (at least) an illiquidity-risk factor; see, among others, Tang and Yan (2008), Bongaerts et al. (2011), Junge and Trolle (2014), and references therein. For instance, in a recent analysis on corporate CDS spreads, Corò et al. (2013) conclude that liquidity risk is even more important than firm-specific credit risk regardless of market conditions. The empirical evidence in the current paper, showing that illiquidity-related factors are largely responsible of pricing errors in non-arbitrage default intensity models, supports the claims in this branch of literature.

This paper also belongs to the literature centered on the analysis of the economic determinants of pricing errors from arbitrage-free pricing models and its diverse implications, particularly in derivative markets. Jarrow, Li and Ye (2011) characterize arbitrage opportunities from a non-arbitrage pricing model under a CIR specification, showing how to implement profitable strategies in this context; see also Duffie (1999). Our paper adopts a different approach and examines the systematic sources of CDS mispricing. The idea of comparing market prices with theoretical prices obtained from a non-arbitrage model to inform about market liquidity is contained in Berenguer, Gimeno and Nave (2013), who study the role of liquidity on the deviations of sovereign bonds yields from a theoretical liquidity-free term structure of interest rates. Within the CDS literature, Nashikkar et al. (2011) approach the CDS-bond basis by computing the difference between market and a theoretically-implied CDS spread under the theoretical constraint of a constant default-intensity model. More recently, Junge and Trolle (2014) construct a measure of market illiquidity in CDS market based on divergences between published credit index levels and their theoretical counterparts.

While we are not aware of other papers dealing with mispricing in CDS markets, several studies have analyzed the drivers of pricing errors in other derivative exchanges. Peña, Rubio and Serna (1999) characterize the determinants of the implied volatility function in European options under the Black-Scholes model. These authors show that the curvature of the implied-volatility function increases on the size of bid-ask spreads, which implies a clear link between pricing errors and transaction costs. Similar results have been reported for other derivative products, such as interest-rate options. The evidence in Deuskar, Gupta and Subrahmanyam (2008) is particularly relevant for our paper because, like CDS contracts, interest-rate options are traded in over-the-counter (OTC) markets, where liquidity-providers are more sensitive to market conditions. Although our methodological approach differs substantially, the overall results completely agree with the general evidence reported in these studies: Pricing errors in derivative contracts are generally sensitive to market-wide illiquidity.

Finally, our paper builds on a price discrepancy measure built in the spirit of Hu et al. (2013). This study complements their paper in two main ways. First, by discussing the generality and suitability of the noise measure, originally implemented in the context of Treasury bond exchanges, in other markets. Secondly, by reporting evidence showing that this measure does indeed correlate with market-wide liquidity conditions from a different methodological approach. While Hu et al. (2013) use the measure in an asset-pricing analysis, we analyze the determinants that ultimately underlie greater price discrepancies in the different context of sovereign CDS markets.

The rest of the paper is organized as follows. Section 2 introduces the noise or pricing discrepancy measure used in our analysis and discusses its suitability for the sovereign CDS market. Section 3 presents the dataset and the econometric framework used to characterize the price discrepancy measure, discussing the main features exhibited by the resultant estimates in the sample. Section 4 analyzes the determinants and the predictability of pricing errors considering a broad set of market-wide indicators. Section 5 conducts several robustness checks. Finally, Section 6 summarizes and concludes.

2. Pricing errors in the CDS term structure

This section formalizes the theoretical relation between CDS spreads at different maturities in an arbitrage-free setting and introduces the main concepts as well as the notation used throughout the paper. It also examines the link between arbitrage capital and pricing errors in CDS markets, introducing the discrepancy or noise measure proposed by Hu et al. (2013), and a discussion on its general suitability in the context of this paper.

2.1. Mispricing and arbitrage opportunities in the CDS term structure

The theoretical arguments used here are primarily taken from Jarrow et al. (2011). To introduce the notation and outline the formal demonstration, consider the price at time t of a CDS with maturity m, denoted $CDS_t(m)$, defined as certain function of the risk-neutral default probability, $\lambda_t^{\mathbb{Q}}$, say $CDS_t(m) = f_t^m(\lambda_t^{\mathbb{Q}})$. Under usual assumptions, a second-order Taylor expansion of the theoretical CDS price function at time $s = t + \Delta t$ yields

$$f_t^m(\lambda_s^{\mathbb{Q}}) = f_t^m(\lambda_t^{\mathbb{Q}}) + (\lambda_s^{\mathbb{Q}} - \lambda_t^{\mathbb{Q}})H_{1t}^m + \frac{1}{2}(\lambda_s^{\mathbb{Q}} - \lambda_t^{\mathbb{Q}})^2 H_{2t}^m + O\left(\left(\widetilde{\lambda}_s^{\mathbb{Q}}\right)^3\right), \qquad (1)$$

where Δt denotes a short period of time, $\widetilde{\lambda}_s^{\mathbb{Q}}$ is a midpoint in the line that joins $\lambda_s^{\mathbb{Q}}$ and $\lambda_t^{\mathbb{Q}}$, and $O(\cdot)$ is a (bounded) remaining term. The terms H_{1t}^m and H_{2t}^m are the first- and second-order derivatives of the pricing function with respect to the default probability, respectively.

According to Jarrow et al. (2011), the current price of a CDS at time s approximates its price at time t, i.e., $f_s^{m-\Delta t}(\lambda_s^{\mathbb{Q}}) \approx f_t^m(\lambda_s^{\mathbb{Q}})$, with $m - \Delta t$ denoting the correction for the maturity time lapse. This assumption enables a connection between the future price of a CDS contract with its current price and certain correcting terms. In particular,

$$f_s^{m-\Delta t}(\lambda_s^{\mathbb{Q}}) \approx f_t^m(\lambda_t^{\mathbb{Q}}) + (\lambda_s^{\mathbb{Q}} - \lambda_t^{\mathbb{Q}})H_{1t}^m + \frac{1}{2}(\lambda_s^{\mathbb{Q}} - \lambda_t^{\mathbb{Q}})^2 H_{2t}^m \tag{2}$$

and, hence, investors could build a delta and gamma-neutral hedging portfolio formed by three default swaps with different maturities, say m_0, m_1 and m_2, such that

$$f_t^{m_0}(\lambda_t^{\mathbb{Q}}) + n_{1t} f_t^{m_1}(\lambda_t^{\mathbb{Q}}) + n_{2t} f_t^{m_2}(\lambda_t^{\mathbb{Q}}) \approx f_s^{m_0-\Delta t}(\lambda_s^{\mathbb{Q}}) + n_{1t} f_s^{m_1-\Delta t}(\lambda_s^{\mathbb{Q}}) + n_{2t} f_s^{m_2-\Delta t}(\lambda_s^{\mathbb{Q}}), \tag{3}$$

where the portfolio weights n_{1t} and n_{2t} are explicitly chosen to form the market neutral portfolio. On average, the theoretical value of portfolio (3) must equal the market price of the portfolio, from which the following relation emerges:

$$\begin{aligned} & \left(f_t^{m_0}(\lambda_t^{\mathbb{Q}}) - CDS_t(m_0)\right) + n_{1t}\left(f_t^{m_1}(\lambda_t^{\mathbb{Q}}) - CDS_t(m_1)\right) + n_{2t}\left(f_t^{m_2}(\lambda_t^{\mathbb{Q}}) - CDS_t(m_2)\right) \\ \approx \; & \varepsilon_t^{m_0} + n_{1t}\varepsilon_t^{m_1} + n_{2t}\varepsilon_t^{m_2}, \end{aligned} \tag{4}$$

with $CDS_t(m_i)$ denoting the observed market prices, and $\varepsilon_t^{m_i} = f_t^{m_i}(\lambda_t^{\mathbb{Q}}) - CDS_t(m_i)$ defined implicitly for $i \in \{0,1,2\}$.

Apart from the tracking error of the strategy, equation (4) shows that discrepancies between the observed and theoretical prices in the CDS curve are directly informative of arbitrage opportunities. As a result, arbitrageurs could design profitable trading strategies involving CDS contracts with different maturities to exploit price discrepancies along the term structure of CDS, as shown empirically in Jarrow et al. (2011). Arbitrage activity, therefore, would align CDS prices along different maturities as to prevent arbitrage opportunities.

2.2. Market frictions and price discrepancies

In practice, the differences between observed and theoretical prices may not necessarily appear as a consequence of a temporary misappraisal of the fundamental value, but also as a consequence of market frictions. Schleifer and Vishny (1997) show that professional arbitrageurs are reluctant to trade under extreme market circumstances as the cost of implementing arbitrage operations can be prohibitive. The main reason is that volatility increases informational asymmetries and exposes arbitrageurs to unwind their positions prematurely, possibly incurring substantial losses. As a result, risk-averse arbitrageurs avoid extremely volatile markets, which reduces the market effectiveness in eliminating differences between fundamental and transaction prices.[2] While many well-known theoretical asset pricing models do not acknowledge transaction costs, in practice these frictions may have substantial effects on prices. This seems to be particularly true in OTC markets, as these exchanges are characterized by a high degree of illiquidity, irregular trading, asymmetric information, and greater counterparty-search costs relative to stock markets; see Duffie, Garleanu and Pedersen (2005) and Tang and Yan (2008) for a discussion.

The possible relationship between market frictions and pricing deviations brings up the issue of capturing these discrepancies empirically. To this end, define $m_1, m_2, ..., m_N$ as an increasing sequence of maturities, and denote as $CDS_t(m_i)$ and $CDS_t^*(m_i)$ the observed CDS spread for the i-th maturity and the corresponding model-implied theoretical price at time t, respectively. Let $CDS_t = (CDS_t(m_1), ..., CDS_t(m_N))'$ be a (N×1) vector collecting the observed CDS spreads representative of the CDS term structure at time t, and define CDS_t^* analogously. Then, the most natural measure of pricing discrepancy is given by the Euclidean distance $\delta_t = ||CDS_t - CDS_t^*||$, i.e.,

$$\delta_t = \sqrt{\sum_{i=1}^{N} \left(CDS_t\left(m_i\right) - CDS_t^*\left(m_i\right)\right)^2} \tag{5}$$

such that $\delta_t = 0$ if and only if all the prices along the curve CDS_t match with the fundamental values, and $\delta_t > 0$ is a proper measure of pricing error otherwise. While a number of transformations can be defined on δ_t, we shall consider the re-scaled distance $noise_{CDS,t} \equiv \delta_t/\sqrt{N}$ proposed in Hu et al. (2013). This variable may also be seen as a sample-based measure of the mean cross-sectional dispersion of the pricing error at time t. The term *noise* was coined by Hu et al. (2013) since, in the fixed-income literature, it is usual to refer to deviations from a given pricing model as noise.

Two main clarifying comments on (5) follow. In first place, Hu et al. (2013) originally proposed the noise measure for Treasury bonds under the the premise that the abundance of arbitrage capital during normal times helps smooth out the Treasury yield curve and keep the average dispersion low. In periods of stress, arbitrage capital vanishes and,

[2]Goldstein, Li and Yang (2013) argue that in highly segmented markets, such as the CDS market, the existence of investors with fairly heterogeneous trading opportunities can lead to multiplicity of equilibria, causing instability in prices.

hence, the average dispersion increases. On the basis of the corresponding noise measure, say $noise_{TBond,t}$, these authors show that the deviations between market and model-based yields are characteristically low –and liquidity correspondingly high– in normal periods, but generally tend to increase during crises as arbitrage capital exits the marketplace. Therefore, the noise measure successfully captures an empirical link between price deviations and arbitrage capital.[3] As argued by Hu et al. (2013), Treasuries provide a particularly good framework to capture global illiquidity, but the information related to this risk factor is not necessarily limited to the Treasury market. For instance, the hedge-fund market may conceivably provide reliable estimates as well since hedge-fund returns decrease during periods of arbitrage capital withdraws; in fact, hedge-fund returns are used to empirically benchmark the explanatory ability of the noise measure in Hu et al. (2013). In our study, we implement (5) in the sovereign CDS market in the belief that the resultant measure would not only be informative on local liquidity and market frictions, but also reflect global trends that feature market illiquidity.

Consistent with this idea, there is an increasing literature arguing that CDS spreads are highly sensitive to market-wide global liquidity conditions; see, for example, Tang and Yan (2008), Bongaerts et al. (2011), and Corò et al. (2013). Net protection sellers such as hedge funds and proprietary trading desks of investment banks are typically the marginal liquidity providers and use the CDS market mainly for speculative purposes. Against a backdrop of decreasing market-wide liquidity and CDS spread widening, however, protection sellers must face pronounced mark-to-market losses and the possibility of incur in costly contract liquidations, which leads to sharp reductions in liquidity provisions. Consistent with this idea, Junge and Trolle (2014) have recently shown that protection sellers require a premium for bearing the risk associated with covariation between CDS returns and market-wide liquidity. Therefore, capital restrictions during periods of global illiquidity make price discrepancies in CDS markets more likely to occur; conversely, sizable pricing errors may be indicative of illiquidity-related distortions that stem from the inability or the unwillingness of market participants to engage in CDS trading rather than being indicative of "true" arbitrage opportunities.

Furthermore, the information on global illiquidity can be tracked more efficiently in CDS markets than it might be in other related markets, such as the corporate bond market.

[3]This measure has been used subsequently in a number of studies; e.g. Filipovic and Trolle (2013).

While bonds are physical assets, CDS are OTC bilateral derivative contracts. This crucial distinction makes CDS markets more liquid along certain dimensions, since CDS prices are less sensitive to convenience yield effects than bond prices, and the notional amount of CDS that can be traded is arbitrarily large; see Longstaff et al. (2011) for a deeper discussion. In fact, whereas the corporate bond market is usually more liquid for bond buyers than it is for short-sellers (due to the need to source a physical asset to reverse repo), the CDS market is equally liquid in both directions. This makes the CDS the preferred instrument for those seeking to implement a short-credit position. More importantly, the extant literature has shown that CDS markets tend to lead bond markets in the price discovery process, i.e., new information tends to be impounded into CDS premia more rapidly. This evidence has been reported for both corporate (e.g., Blanco et al. (2005); Forte and Peña, 2009) and sovereign markets (Delatte, Gex and López-Villavicencio (2012), Gyntelberg, Hördahl, Ters and Urban (2013); and IMF, 2013). Consequently, the average dispersion of CDS spreads should be expected to be low during normal periods, when arbitrage capital actively contributes to align CDS spreads, and high in turmoil periods, when arbitrage capital exits the market. In that case, abnormally high values of $noise_{CDS,t}$ may be related to episodes of market-wide illiquidity and local or global shortage of arbitrage capital.

In second place, characterizing (5) requires prices generated by a theoretical term-structure pricing model. We focus initially on the continuous-time, arbitrage-free CDS pricing model of Pan and Singleton (2008), referred to as the PS model in the sequel. The distinctive characteristic of this pricing model is that it yields a full theoretical term structure of CDS spreads consistent with the no-arbitrage condition that overperforms other alternative approaches; see, for example, Longstaff et al. (2011). A priori, it seems reasonable to expect that sensible choices of alternative pricing models would lead to similar patterns in the resultant pricing errors. However, since this is ultimately an empirical issue, we shall address the robustness of the main conclusions based on Pan and Singleton (2008) by focusing on alternative term structure pricing models that differ in complexity and underlying assumptions. This will be extensively discussed in Section 5.2.

3. Estimating the noise measure

3.1. The data

Default swaps are a well-known class of OTC derivatives traded for investing and speculating single name default risk at different maturities. The CDS market has undergone tremendous expansion over recent years, now accounting for more than two thirds of all outstanding credit derivatives (Goldstein et al., 2013). Although sovereign CDS trading constitutes a relatively small share of this market, its importance has grown rapidly since the 2007-2008 financial crisis owing to increasing concerns about default in Treasuries and bonds issued by advanced economies; see IMF (2013).[4] A typical CDS contract on sovereign debt specifies that a buyer, in exchange for an annual fee set by the market and paid quarterly, obtains from a seller specified credit protection against default and broadly similar credit events affecting securities issued by a reference country. The CDS spread represents the annual percentage over the total amount of the bond (notional) paid to the seller for obtaining protection in case of a credit event occurs. Such events include failure to pay, repudiation or moratorium on debt, and certain debt restructurings.

The dataset analyzed in this paper consists of an unbalanced panel of weekly sovereign CDS spreads from 16 economies of the G-20 group: Argentina, Australia, Brazil, China, France, Germany, Indonesia, Italy, Japan, Mexico, Saudi Arabia, South Africa, South Korea, Spain, UK and US. The choice of the weekly frequency aims to avoid potential caveats related to the low trading activity at daily frequency of most sovereign CDS contracts.[5] The sample initially available spans the period from January 1st, 2006 to November 9th, 2012 and includes 358 weekly observations for most of these countries. The data for some countries (Saudi Arabia, UK, and US) is available on a shorter period and includes a smaller number of observations, ranging from 228 (Saudi Arabia) to 257 (US) data. The maturity spectrum of CDS contracts in the sample comprises all available maturities from one to ten years. All contracts are denominated in US dollars and written under the Complete Restructuring clause. Data have been provided by Credit Market Analysis (CMA), a quote provider integrated in the Datastream platform.[6]

Together with CDS spreads, we observe different variables related to trading activity

[4]For instance, the rating agency Standard & Poor's downgraded the US sovereign credit rating from AAA to AA+ in June 2011, giving rise to the first downgrade in the nation's history. Similarly, the agency downgraded the rating of nine Euro-zone countries in January 2012, stripping France and Austria from the AAA rating, and relegating the sovereign debt of Portugal and Cyprus to junk status.

[5]Chen, Fleming, Jackson, Li and Sarkar (2011) analyze the distribution of total trading frequency of sovereign CDS contracts across all maturities. From a total of 74 reference entities, just four are actively traded on average 30 times daily; and 14 out of 74 are less actively traded, at 15 times per day on average. The remaining sovereign references are infrequently traded at an average of twice daily.

[6]The CMA database collects daily reports on bid, ask and mid-quotes of CDS spreads from a robust consortium that consists of approximately 40 members from the buy-side community (hedge funds, asset managers, and major investment banks), which are active participants in the CDS market.

and liquidity for any of the sovereign CDS included in the sample. These data are provided by the Depository Trust & Clearing Corporation (DTCC) since November 2008. More specifically, we observe both the gross and net notional CDS positions, and the number of outstanding contracts in the CDS market. The gross notional value is the aggregate sum of the CDS contracts bought or sold for a single reference entity. The net notional values represents the aggregate net funds transference between protection sellers and buyers that could be required upon the occurrence of a credit event relating to a particular reference entity. Finally, the number of contracts reports the outstanding number of contracts for a given reference. A complete description of the dataset is provided in the online Appendix A of this article.

3.2. Theoretical CDS spreads and econometric estimation

The empirical implementation of the noise measure (5) requires model-implied theoretical prices. Most of the pricing models for CDS spreads in the extant literature strive essentially to capture default risk and the potential loss upon default, similarly to that of credit spreads for corporate bonds. The intensity framework of Duffie and Singleton (1999) and Lando (1998) seems to be the most popular pricing framework. Under this approach, the default event is modeled as the first jump of a Poisson process with stochastic default intensity $\lambda_t^{\mathbb{Q}}$, where $\mathbb{Q}$ denotes the risk-neutral measure. Then, the (annualized) price of a CDS contract for maturity m at time t obeys the relation,

$$\frac{1}{4} CDS_t(m) \sum_{i=1}^{4m} E_t^{\mathbb{Q}} \left[\exp\left(- \int_t^{t+\frac{i}{4}} (r_s + \lambda_s^{\mathbb{Q}}) ds \right) \right] = (1 - \mathbb{R}^{\mathbb{Q}}) \int_t^{t+m} E_t^{\mathbb{Q}} \left[\lambda_u^{\mathbb{Q}} \exp\left(- \int_t^{u} (r_s + \lambda_s^{\mathbb{Q}}) ds \right) \right] du \qquad (6)$$

where r_t and $\mathbb{R}^{\mathbb{Q}}$ denote, respectively, the risk-free interest rate and the recovery of face value (in percentage) of the referenced bond under the risk-neutral measure; see, among others, Longstaff et al. (2005) and Pan and Singleton (2008). The left-hand side of this equation represents the premium on the sum of expected discounted cash-flows paid by the protection buyer under the risk-neutral measure. This premium is the CDS spread and is quarterly. The right-hand side accounts for the expected discounted payoff received by the protection buyer in case of a default event. Single-name CDS contracts are written without up-front payments, which equals both sides of expression (6).

In this setting, Pan and Singleton (2008) propose an intensity model which presents remarkable advantages over other affine pricing models. While the CIR process has been extensively employed in this context as it provides closed-form formulas (e.g., Longstaff et al., 2005), the Feller condition bounds the long-term mean of the CIR-based intensity to the square-root of its long-term variance, a requirement frequently violated in practice. The PS model not only overcomes this drawback, but also provides a good compromise between model parsimony and performance in a comparison of several one-factor intensity models. For these reasons, and although we stress that we shall consider alternative modeling approaches later on, the arbitrage-free PS model is the pricing benchmark chosen for characterizing empirically price discrepancies in the sovereign CDS market. We provide a brief discussion on the implementation of this model below.

The PS model assumes that the logarithm of the risk-neutral default intensity $\lambda_t^{\mathbb{Q}}$ follows an Ornstein-Uhlenbeck diffusion process characterized by

$$d\ln\lambda_t^{\mathbb{Q}} = \kappa^{\mathbb{P}}\left(\theta^{\mathbb{P}} - \ln\lambda_t^{\mathbb{Q}}\right)dt + \sigma^{\mathbb{Q}} dW_t^{\mathbb{P}}, \tag{7}$$

where $\kappa^{\mathbb{P}}$ and $\theta^{\mathbb{P}}$ are the long-run mean, and mean-reversion rate of the process under the actual or historical measure $\mathbb{P}$, respectively, with $\sigma^{\mathbb{Q}}$ denoting the volatility of the process and $W_t^{\mathbb{P}}$ a standard Wiener process. The model also characterizes the dynamics of (7) under the risk-neutral measure $\mathbb{Q}$,

$$d\ln\lambda_t^{\mathbb{Q}} = \kappa^{\mathbb{Q}}\left(\theta^{\mathbb{Q}} - \ln\lambda_t^{\mathbb{Q}}\right)dt + \sigma^{\mathbb{Q}} dW_t^{\mathbb{Q}}, \tag{8}$$

and the market price of risk, say Λ_t, defined through the affine function $\varphi_0 + \varphi_1 \ln\lambda_t^{\mathbb{Q}}$, where φ_0 and φ_1 denote constant parameters. The process (8) ensures the positiveness of risk-neutral default intensity. However, the expectations in CDS formula (6) are not in closed-form, so numerical techniques as the Crank-Nicholson scheme are required.

The parameters that characterize the PS model can be estimated by maximum likelihood given a number of additional assumptions. The reader is referred to the original paper for details, but we briefly sketch the main steps involved in the estimation of this model in the sequel. In particular, the PS procedure assumes that CDS contracts at a certain maturity are priced with no error, whereas prices at the remaining maturities can be determined under non-arbitrage conditions. These authors employ the 5-year maturity for extracting the default discount process. This choice is arbitrary, but based on the sensible appreciation that the 5-year contract is the most heavily traded tenor in practice. We follow Pan and Singleton (2008) and assume this contract is free of pricing errors.[7] Then, a series of the probability of default $\lambda^{\mathbb{Q}}$ can be obtained by solving (6) for this coefficient. This involves non-linear numerical techniques, using the 3-, 6-, 9- and 12-month USD Libor and 2-, 3-, 4-, 5-, 7- and 10-year USD interest rate swaps to construct the risk-free curve that characterizes (6). The remaining CDS contract maturities are assumed to be priced with random errors $\varepsilon_{m,t}$ that obey a normal multivariate distribution with zero mean vector and covariance matrix $\sigma_M^2 I_{N-1}$, where I_{N-1} denotes the $N-1$ dimensional identity matrix and N is the number of different maturities. For parsimony and computational tractability, we assume that σ_M is constant across maturities, noting however that results do not qualitatively differ from more general specifications (results under heteroskedasticity are available upon request). The estimation of this model also requires the discretization of $\lambda^{\mathbb{Q}}$ in expression (7), for which we adopt the Euler's approach and set $\Delta t = 1/52$. Then, the unknown parameters $\psi = (\psi^{\mathbb{P}}, \psi^{\mathbb{Q}}, \sigma_M)'$, with $\psi^{\mathbb{P}} = (\kappa^{\mathbb{P}}, \theta^{\mathbb{P}})'$, $\psi^{\mathbb{Q}} = (\kappa^{\mathbb{Q}}, \theta^{\mathbb{Q}}, \sigma^{\mathbb{Q}}, \mathbb{R}^{\mathbb{Q}})'$, can be estimated by maximizing the conditional log-likelihood function $\sum_{t=2}^{T} \ln f^{\mathbb{P}}(\varepsilon_{m,t}|\psi, \mathscr{F}_{t-1})$, with $\mathscr{F}_{t-1}$ denoting the set of available information up to t, and

$$f^{\mathbb{P}}(\varepsilon_{m,t}|\psi, \mathscr{F}_{t-1}) = \phi^{\mathbb{P}}(\varepsilon_{m,t}|\sigma_M, \mathscr{F}_{t-1}) \times \phi^{\mathbb{P}}(\ln \lambda_t^{\mathbb{Q}}|\psi^{\mathbb{P}}, \sigma^{\mathbb{Q}}, \mathscr{F}_{t-1}) \times \left| \frac{\partial CDS^{\mathbb{Q}}(\lambda^{\mathbb{Q}}|\psi^{\mathbb{Q}}, \mathscr{F}_{t-1})}{\partial \lambda_t^{\mathbb{Q}}} \right|^{-1} \tag{9}$$

where $\phi^{\mathbb{P}}(\cdot)$ denotes the probability density function of the Normal distribution, $\lambda_t^{\mathbb{Q}}$ as given by expression (7), and $CDS^{\mathbb{Q}}(\cdot)$ in formula (6).

Table 1 reports the maximum-likelihood estimates of ψ (robust standard errors in parenthesis) for the different sovereigns CDS in the sample. The mean-reversion speed estimates under the actual measure, $\kappa^{\mathbb{P}}$, are higher than the mean-reversion speed coefficients under the risk-neutral measure, $\kappa^{\mathbb{Q}}$, indicating that the arrival of credit events last longer under this measure. Moreover, the long-run mean estimates are also higher under the risk-neutral measure ($\kappa^{\mathbb{Q}}\theta^{\mathbb{Q}} > \kappa^{\mathbb{P}}\theta^{\mathbb{P}}$), suggesting that the arrival of events in the risk-

[7] As discussed by Longstaff et al. (2011), this choice is not expected to have a major effect in the estimations. We checked this issue in our context by conducting independent estimations assuming extreme scenarios in which the 1- and 10-year maturities were correctly priced. The average correlation between the resultant noise series and that employed in the article is higher than 80% in all cases.

neutral scenario is more probable than in the actual one. In other words, a positive risk premium related to changes in the credit environment seems to be priced in the sovereign CDS market. Finally, the recovery rate $\mathbb{R}^{\mathbb{Q}}$ tends to be closely related to the creditworthiness of the country: South Korea, South Africa, Germany, France and UK exhibit the highest value (around 80%), in contrast to Argentina and Spain (around 3%). Overall, the PS model yields reasonable estimates that are coherent with related studies in the extant literature; see, for instance, Pan and Singleton (2008) and Longstaff et al. (2011).

[TABLE 1 ABOUT HERE]

3.3. Main results

Figure 1 shows the time series dynamics of the 25%, 50%, and 75% percentiles of the PS-implied $noise_{CDS,t}$ measure. To account for structural differences, we split the total sample into the groups formed by Advanced Economies (henceforth AE, including Australia, France, Germany, Italy, Japan, Spain, UK, and US) and Emerging Economies (henceforth EE, formed by the remaining countries in the sample). The cross-section median of $noise_{CDS,t}$ in both groups is characterized by a strongly non-linear, globally mean-reverting pattern which can be associated to latent dynamics that determine whether the economy is in a normal or stressed regime.[8] Pricing errors tend to have a low dispersion during normal periods, but they largely increase during stress periods, peaking after systemic episodes such as the collapse of Lehman Brothers in September, 2008, or the Greek bailout in March, 2010. This evidence completely agrees with the results reported by Hu et al. (2013). On average, pricing discrepancies tend to be greater and much more volatile in the EE group, but it is clear that the AE- and EE-related noise measures exhibit common patterns and follow a similar trend.

[INSERT FIGURE 1 ABOUT HERE]

Table 2 reports standard descriptive statistics of the estimates of the noise measure for any of the sovereign CDS analyzed. The overall mean value is 13.08 basis points, but there is a strong heterogeneity across countries. The individual averages range from

[8] The non-linear, mean-reverting path of the noise series is even more evident in the analysis of $noise_{TBond,t}$ in Hu et al. (2013) because the sample analyzed therein spans a longer period, from 1987 through 2011. Over this period, $noise_{TBond,t}$ is shown to spike prominently as a consequence of shocks related to crises, and revert to the mean level afterwards.

4.52 (Germany) to 85.70 basis points (Argentina). Furthermore, the volatility of $noise_{CDS,t}$ largely varies from distressed to resilient economies, showing the largest differences for Argentina, Indonesia, Italy and Spain. In contrast, solid economies in advanced countries, such as US or Germany, show the smallest degree of average dispersion in pricing errors. The largest value of the noise measure in Argentina reaches 1111.39 basis points, whereas US peaks at 17.22 basis points. Clearly, the noise measure is related to the factors that characterize whether the CDS spread has a large mean value and high dispersion or not.

[INSERT TABLE 2 ABOUT HERE]

Since, as discussed previously, short-term maturities exhibit larger idiosyncratic patterns, it is interesting to analyze whether CDS maturities contribute equally to price divergences. The existence of a systematic mispricing of CDS contracts of a given maturity could indicate the existence of pricing factors not captured by the model (Pan and Singleton, 2008). To address this question, we define the relative contribution of maturity m_τ to the noise measure as $\omega_t(m_\tau) = |CDS_t(m_\tau) - CDS_t^*(m_\tau)| / \delta_t$, $\tau = 1, ..., 10$, with δ_t as defined in (5), and noting that $0 \leq \omega_t(m_\tau) \leq 1$ and $\sum_{\tau=1}^{10} \omega_t(m_\tau) = 1$. Recalling that the PS model assumes no pricing error at the 5-year maturity, it follows by construction $\omega_t(5) = 0$, and it should be understood that the relative contributions of the remaining maturities are conditional to this assumption.

Table 3 reports basic time-series statistics (mean, median and standard deviations) of $\omega_t(m_\tau)$ for each maturity and each country in the sample. This table also reports the maturity for which the relative contribution $\omega_t(m_\tau)$ is the largest. According to these results, the 1-year maturity contract systematically exhibits the highest contribution to the noise measure in most countries.[9] The average relative contribution of the pricing errors to the total ranges from 26.93% in US to 59.20% in Argentina. In their study focused on the emerging economies of Mexico, South Korea and Turkey, Pan and Singleton (2008) reported evidence of large 1-year maturity CDS mispricing, arguing that this feature is related to limited cash vehicles with which to hedge such instruments, which erodes the ability of arbitrageurs to engage in effective strategies. Our results agree with these findings (showing large relative contributions of the 1-year CDS to the total error of about 60.15% and

[9] Australia, China and US seem to be rare exceptions. Even though the noise is concentrated at longer maturities for these countries, the standard deviation of the noise contribution to the 1-year maturity is still the highest across maturities.

46.70% in Mexico and South Korea, respectively) and further generalize them by showing that short-term mispricing tends to apply systematically in the remaining economies included in our sample, whether emergent or not.

[INSERT TABLE 3 ABOUT HERE]

Before a more formal analysis is conducted, it is worth analyzing the existence of commonalities in pricing errors through simple descriptive techniques. Being obtained from pricing errors, no systematic pattern across countries should be observed. However, the principal component analysis on the standardized noise series reveals the existence of a first principal component able to explain approximately 33% of the total variation. This share increases to 56% and 65% when the second and third components are included, respectively. The loading coefficients on the first principal component (not reported here but included in the online Appendix B of this article) could be interpreted as a world-wide market trend, since all the countries except Brazil and China exhibit positive loadings. The loadings on the second principal component exhibit a heterogeneous behavior that can be related to creditworthiness: Loadings tend to be positive or mildly negative for countries in which the noise measure exhibits low mean values and low volatility, such as France, Germany, UK, and US, and are mostly negative for countries in which pricing errors have a relatively high mean and high volatility, such as most countries in the EE group and distressed economies in peripheral Europe, such as Spain.

The strong degree of commonality suggests the existence of risk factors which are not properly captured by the theoretical model but which, nevertheless, are systematically priced in the CDS market. To gain further insight into the sources of this commonality and its economic interpretation, we project the time series increments of the first principal components, denoted as ΔPC1, on the increments of a set of market-wide global state variables sampled from the US market over the period December 2007 to November 2012. Using variables from the US market to proxy for global conditions in this preliminary analysis seems reasonable because of the strong degree of globalization in financial markets and the predominance of the US economy (see, among others, Rapach, Strauss and Zhou, 2013). Nevertheless, we stress that a more rigorous analysis, building on country-specific variables in a panel-data approach, shall be conducted in the next section. The explanatory variables used in this preliminary analysis are the changes in the volatility index of the Chicago Board Options Exchange (*VIX*), used as an indicator of global uncertainty; the change in Moody's bond spread index between AAA and BBB bonds (*Default*), used as a proxy for corporate default spread; the return of the Dow Jones Index (*MarketReturn*), used as a natural indicator of stock market performance and market risk; the change in the first principal component of net notional volumes (*PC1netvol*), and the change in the first principal component of bid-ask spreads at 5-year maturity (*PC1BA5y*), both of which are used as different proxies of aggregate market-wide liquidity. All these variables are sampled weekly.

Table 4 reports the main statistical outcomes (estimates, Newey-West robust standard errors and adjusted R^2) from the individual regressions of ΔPC1 on a constant and any of the state variables considered. Recall that the first principal component captures the main source of common variation in cross-country sovereign CDS mispricing. All these variables except increments in *PC1netvol* are highly significant, with adjusted R^2 ranging from a conservative 5% (Δ*Default*) to a large 21.79% (*MarketReturn*). Table 4 also reports the results from the joint regression of ΔPC1 on all the state variables. The estimates reveal a significantly and positive association with increments in *VIX*, and a significantly and negative association with market returns and increments in the first principal component of net volume. The adjusted R^2 increases up to 25.75%. The overall picture that emerges from this analysis shows that against a backdrop of increasing volatility, large market losses, and increasing number of offsetting operations in the sovereign CDS market (i.e., a characteristic scenario of financial distress), the conditional mean of the first principal component tends to increase. This is coherent with the hypothesis that the noise measures computed from CDS spreads are (partially) driven by systematic sources of financial risk mainly related to excess volatility and market-wide illiquidity. Remarkably, the overall evidence from this analysis is completely similar to that reported by Hu et al. (2013) on the variables that drive price discrepancies as captured by the noise measure in the different context of Treasury markets.

[INSERT TABLE 4 ABOUT HERE]

The main conclusions from this preliminary analysis allows us to conclude that price discrepancies exhibit a strong time-varying pattern which increases substantially during distress periods. Pricing errors are on average largely contributed by discrepancies at the 1-year maturity, which could be related to market frictions and trading barriers that generally pose limits to the arbitrage. More importantly, the principal component analysis reveals a strong source of cross-country commonality driving pricing discrepancies that can be related to market-wide stress conditions characterized by high volatility, negative market performance, and liquidity withdraws. This evidence shows a characteristic scenario which fits squarely with the theoretical predictions in Schleifer and Vishny (1997), showing that larger pricing errors can systematically be related to adverse economic scenarios. These conclusions, based on a simple and direct analysis, will be confirmed in a more rigorous analysis based on panel-data regressions in the next section.

4. Determinants of pricing errors in sovereign CDS markets

The main objective of this paper is to examine the economic determinants of pricing errors in the sovereign CDS term structure. To this end, we implement different estimation procedures within the panel-data methodology that regress a log-transform of the noise measure on either contemporaneous or lagged values of illiquidity-related variables. Our main aim is to parsimoniously address the existence of an empirical relationship between price discrepancies and market-wide illiquidity, considering mainly country-specific variables that capture local information on the liquidity conditions in the CDS market as well as other potential global control variables.

4.1. State variables

We consider a panel of country-specific and global variables that can be grouped into the categories of market-wide illiquidity and market uncertainty. The set of illiquidity-related variables include *i*) the 5-year maturity bid-ask spreads (*Bidask*), *ii*) Number of Traded CDS contracts (*Contracts*), and *iii*) Net Notional Outstanding Volume (*Netvol*). All these variables are country-specific and are available from DTCC.

The set of of market uncertainty-related variables include *iv*) a local proxy of market volatility (*Marketvol*), as measured by the absolute value of the weekly market index return, and *v*) a global indicator of default premium (*Default*), characterized as the price spread between AAA and BBB rated US investment, as discussed previously. It should be noticed that this set of variables suffices to explain a remarkably large proportion of variability, since price discrepancies turn out to be strongly related to country-specific drivers which characterize liquidity. As discussed in the robustness section, taking further macroeconomic and financial variables into account, most of which are only available at the global level, does not seem to improve results nor lead to qualitative differences in the main results. We discuss the variables used in the panel-data regressions in the remainder of this subsection.

All the variables in the liquidity group are strongly correlated and share a considerable degree of commonality. Although they all can be related to liquidity risk, they measure different facets of this magnitude (Chordia, Roll and Subrahmanyan, 2001). In particular, *Bidask*, the most popular indicator of illiquidity in security markets, is a measure of the tightness of asset prices. According to the extant literature, bid-ask spreads include two components. One is the compensation required by market-makers for inventory costs, clearing fees, and/or monopoly profits. The second one results from a characteristic adverse-selection problem faced by market-makers in a context of asymmetric information. It mainly represents the additional compensation for the expected costs caused by informed-trading activity. Hence, in periods of greater price uncertainty in which informed investors can profit from their superior information, bid-ask spreads tend to widen and lead to greater transaction costs. Acharya and Johnson (2007) report evidence of informed-trading activity in the CDS market. Furthermore, this information flows to equity markets in response to negative credit news, suggesting that price discovery for those events tends to happen in CDS markets. Consequently, we expect a positive relation with mispricing, since liquidity providers can exit the market when transaction costs are high; see Longstaff et al. (2005), Chen, Lesmond and Wei (2007), and Tang and Yan (2008).

The variable *Contracts* is a measure of market-wide trading activity and, therefore, can be deemed to be an indirect measure of liquidity. In general terms, trading activity induces price volatility, so the number of trades has been often related to noise trading. Furthermore, Tang and Yan (2008) use this variable to proxy for the overall inventory in the CDS market, which could also be related to holding costs. In the inter-dealer market, inventory control may be a major concern for dealers under funding constraints, as this may impair the capacity for dealers to take sides in additional contracts and thereby affect the liquidity of the related contracts; see Brunnermeier and Pedersen (2009). Finally, Oehmke and Zawadowsky (2013) argue that the illiquidity of the bond market increases the amount of CDS outstanding, since CDS contracts should be more heavily used when the underlying bond is illiquid – and thus hard or expensive to trade. According to all these considerations, we should expect a positive relation with higher price discrepancies.

The variable *Netvol* reflects the net total amount exchanged in case of default. In contrast to the gross notional outstanding volume, which increases with every trade, the net notional volume adjusts the gross notional amount for offsetting positions. In this way, the net notional turns out to be an excellent indicator of the overall amount of credit risk transfer in the CDS market. As discussed by Oehmke and Zawadowsky (2013), an intuitive way to interpret the *Netvol* variable is to consider it as the maximum amount of payments that need to be made between counterparties in the case of a credit event on a particular reference entity. As in other derivative markets, such as the futures market, entering offsetting trades in the CDS markets is a more common way to reduce exposures than canceling an existing CDS contract. Because arbitrageurs unwind positions during extreme circumstances, effective reductions in net traded volumes should be related to larger pricing errors. This variable could inversely proxy for the unobservable holding costs (including, for example, the opportunity cost of capital, the opportunity cost of not receiving full interest on short-sale proceeds, and idiosyncratic risk exposures), with arbitrageurs closing positions when these costs increase excessively.

Together with these variables, we consider the country-specific variable *Marketvol* to capture market-wide volatility in the local stock market. Market volatility is a latent factor particularly sensitive to the information flow which subsumes information relative to collective expectations, environmental conditions, and market sentiment. Consistent with the results reported in the previous section and the theoretical considerations in Schleifer and Vishny (1997) and others, we expect volatility to be a natural driver of the noise measure. Accordingly, larger levels of volatility lead to greater pricing errors. Additionally, the variable *Default*, calculated using the Moody's bond spread index for 3-5 year maturity bonds, is a global proxy to capture time-varying default premium; see Hu et al. (2013). Notice that, since the noise measure is obtained from the residuals of a theoretical default-risk model, this variable must not be significant if default risk is correctly priced on average by the model. Hence, the analysis on this variable provides a diagnosis test about the empirical performance of the PS model.

4.2. Analysis of determinants and short-term predictive power

Let $\ln noise_{CDS,it}$ denote the natural logarithm of the sample estimate of the $noise_{CDS}$ measure for the i-th country at time t. We model the conditional mean of this process as a linear function of the state variables building on a panel-data model specification. Acharya and Johnson (2007) and Tang and Yan (2008) use a similar approach to identify the main determinants of CDS spreads, rather than CDS spread pricing errors; see also Chiaramonte and Casu (2013). The specification is similar in spirit to the determinant models used, for instance, in Peña et al. (1999) and Deuskar et al. (2008), although our approach builds on direct estimates of pricing errors. In particular, we consider the following regression specification, referred to as Model I in the sequel,

$$\begin{aligned} \ln noise_{CDS,it} &= \alpha + \phi \ln Bidask_{it} + \beta_1 \ln Contracts_{it} + \beta_2 \ln Netvol_{it} \\ &+ \beta_3 Marketvolatility_{it} + \beta_4 Default_t + \eta_i + \varepsilon_{it} \end{aligned} \tag{10}$$

or, using a more convenient notation,

$$\ln noise_{CDS,it} = \alpha + \phi \ln Bidask_{it} + \beta' X_{it} + \eta_i + \varepsilon_{it}, \tag{11}$$

where η_i represents country-specific effects that are constant over time but can vary across countries, $\theta = (\alpha, \phi, \beta')'$, with $\beta = (\beta_1, ..., \beta_4)'$, denotes the vector of unknown parameters, ε_{it} is a disturbance assumed to obey standard assumptions, and X_{it} is a vector of explanatory variables defined implicitly.

Some brief comments follow. While bid-ask spreads are stationary series, the vector X_{it} includes strongly-persistent variables which may be driven by stochastic or deterministic trends, such as ln*Contracts*, ln*Netvol*, *Marketvolatility* and *Default*. In order to ensure that this feature does not impose any meaningful distortion in the main conclusions from (11), we will consider an alternative specification that builds on first differences of these variables. The log-transform is applied to reduce the effects of outliers and heteroskedasticity in the series. Note that, as a result, the coefficients associated to regressors in logarithms can be interpreted as the elasticity of $noise_{CDS,it}$ with respect to the related variable. Finally, this specification does not include gross volume, initially available in DTCC, because this variable has a correlation coefficient of 85% with $Contracts$. We exclude that variable to avoid colinearity-related concerns, noting that $Contracts$ shows a greater sample correlation to the dependent variable (36%), yet a smaller correlation to the other explanatory variables than gross contracts does.

Since X_{it} is a strongly persistent vector process with high first-order autocorrelation coefficients, for the sake of robustness, we consider an alternative specification to (11) in which persistent variables are plugged in differences, namely,

$$\ln noise_{CDS,it} = \alpha^* + \phi^* \ln Bidask_{it} + \beta^{*\prime} \Delta X_t + \eta_i + u_{it} \tag{12}$$

with $\Delta X_{it} = X_{it} - X_{it-1}$. Since bid-ask spreads and the dependent variable are stationary, they are left in levels. The resultant model shall be referred to as Model II in the sequel.

The parameters that characterize equations (11) and (12) are initially estimated using three different procedures aiming to control for cluster errors, unobservable individual heterogeneity, and endogeneity. In particular, we first consider pooled time-series cross-sectional regressions with two-way cluster-robust standard errors accounting for country and week clusters. This methodology allows us to carry out statistical inference which is robust to fairly general simultaneous dependencies of unknown form in both the cross-sectional and time-series dimensions of the panel; see Petersen (2009). Furthermore, this methodology seems particularly useful in the empirical context of this paper, characterized by a panel with a larger number of time-series observations than individuals. We can readily control for unobservable heterogeneity using individual dummies to estimate the coefficients η_i, since the Haussman test largely favors fixed-effect over random errors. Second, consistent with model specification testing, and as is common in the related literature, we consider fixed-effects panel-data regressions with robust errors to autocorrelation and heteroskedasticity.[10] The resultant estimates are remarkably similar to those obtained under the first approach. Lastly, we consider IV estimation in the fixed-effects panel data, using a single lag of the variables as an instrument in order to mitigate concerns related to endogeneity. The results from a more sophisticated analysis, based on GMM estimation and building on multiple instruments, shall be discussed later in the robustness analysis section.

In addition, we analyze the predictive ability of the variables in Model I and II to forecast the dependent variable. To this end, we regress $\ln noise_{CDS,it}$ on lagged values of all the right-hand side variables in equations (11) and (12), i.e., we consider predictive panel-data regressions to appraise whether the state variables are useful to predict price discrepancies given the set of available information. Consequently, and paralleling equations (11) and (12), we consider the predictive equations:

$$\ln noise_{CDS,it} = \alpha_l + \phi_l \ln Bidask_{it-1} + \beta_l' X_{it-1} + \eta_i + v_{it} \qquad (13)$$

[10] Panel data with random errors can be seen as a more general specification than fixed errors. We implemented both approaches, noticing no qualitative difference in the main conclusions discussed below. However, since the Haussman test largely favors fixed-effect over random errors in our sample, we report and discuss the resultant estimates from this model.

and

$$\ln noise_{CDS,it} = \alpha_l^* + \phi_l^* \ln Bidask_{it-1} + \beta_l^{*\prime} \Delta X_{t-1} + \eta_i + w_{it} \tag{14}$$

with $\theta_l = \left(\alpha_l, \phi_l, \beta_l'\right)'$ and $\theta_l^* = \left(\alpha_l^*, \phi_l^*, \beta_l^{*\prime}\right)'$ denoting the main parameters of interest, and v_{it} and w_{it} being random disturbances. Because (13) and (14) are trivial variations of Models I and II, respectively, we shall simply refer to this approach as predictive two-way cluster when reporting the main results. All model estimations are carried out using a noise measure estimated for the period November 4th, 2008 to November 9th, 2012, due to the data availability restrictions on the set of explanatory variables used in the analysis.[11]

4.3. Main results

Table 5 reports the main outcomes from the regression analysis (estimated parameters, robust p-values of the t-statistic for individual significance, and R^2), using the different estimation techniques discussed previously and the model specifications (11) to (14). For ease of exposition, we shall present and discuss the parameter estimates from the two-way cluster methodology with country dummies and robust standard errors to unknown heteroskedasticity and correlation. Let us first discuss the results for Model I and its predictive variation, corresponding to equation (11) and (13), respectively. These are reported in the bottom part of the table (Panel A). Independently of the estimation technique, the results show that larger bid-ask spreads, greater trading activity, and greater netting activity within counterparties are systematically related to greater pricing errors. A relative increment of 100 basis points in the bid-ask spread leads, on average, to an increment of nearly 50 basis points in the dispersion of pricing error, everything else being equal. Similarly, the noise measure has a elasticity coefficient of 0.58 and -0.32 with respect to the number of contracts and net notional CDS positions, respectively. These estimates are both statistically and economically significant, and confirm a unmitigated influence of liquidity-related factors on pricing errors in the CDS markets. Owing to the importance of this result, we shall discuss its implications in detail later on, after presenting the remaining estimates.

[INSERT TABLE 5 ABOUT HERE]

As expected, the proxy for local market volatility in stock markets, used mainly as control in our analysis, is positively related to CDS price discrepancies. The statistical

[11] We have also constructed two subsamples using the entire CDS dataset and the reduced one for estimating the noise measure. The results do not differ in any case.

significance of the related coefficients is marginal in contemporaneous regressions, and non-significant in the predictive model. While using a robust, but noisy proxy of the unobservable volatility based on absolute-valued weekly returns is likely to increase standard errors, the apparent lack of significance of this variable is actually related to the (positive) correlation that volatility shows with the *Bidask* variable. If the latter is omitted from the regression analysis (results not presented for the sake of saving space), then the coefficient on *Marketvolatility* is positive and strongly significant in all cases, suggesting the *Bidask* partially overrides the information conveyed by volatility. Similarly, the significance tests of *Default* cannot be rejected in most cases at the usual significance levels. The potential information conveyed by the global variable *Default* may be subsumed in the remaining variables as well, but it is fair to attribute the lack of significance of this variable to a correct performance of the PS model, this result evidencing that the time- and cross-section variation of the PS-based noise measure is not driven by poor CDS-spread curve fitting. The analysis on the predictive regression shows that illiquidity-related variables can be used as reliable short-term predictors of future mispricing. IV-based estimation leads to an entirely similar picture; see also GMM-based results reported in the robustness section. Finally, the analysis of the R^2 shows that the models are extremely parsimonious, since a reduced number of country-specific variables, mainly related to market-wide illiquidity, are able to achieve a R^2 of approximately 95% in explaining price discrepancies.

The main results from the estimation of Model II are reported in the bottom part of Table 5, see Panel B. Recall that the only difference with respect to the previous models is that the dependent variable is regressed on Bidask_{it} and ΔX_{it} in the contemporaneous regression, and on Bidask_{it-1} and ΔX_{it-1} in the predictive regression. The resultant estimates show that relative increments in bid-ask spreads can be consistently related to larger price dispersion in the CDS curve. When bid-ask spreads widen, arbitrage becomes more costly, likely reducing arbitrage activity. As we shall see discuss later in Section 5 throughout the different robustness checks, this is one of the most robust findings of the paper. Similarly, changes in net notional CDS volumes are negatively related to price dispersion, indicating further illiquidity-related distortions, as discussed previously. In this case, statistical evidence supporting the inclusion of this variable is marginally significant in two-way cluster estimation, but strongly significant through the remaining estimation procedures, particularly, under IV estimation. This ambiguous evidence merits further attention and shall be explored in greater detail in the robustness section. The variables *Contracts* and *Default* do not seem to play any meaningful role after accounting for other factors, and once more market volatility is positively but not significantly related to the noise measure. As in Panel A, this evidence is robust to different estimation techniques and remains valid even when considering lagged values of these state variables in a predictive regression.

In summary, the price discrepancies of observed CDS spreads with respect to the PS-implied theoretical prices do significantly covariate with state variables that characterize illiquidity in the sovereign CDS market. This relation is so strong that illiquidity-related variables can be used as reliable predictors of mispricing in the short-term. The evidence is particularly significant for bid-ask spreads, as generally expected from the theoretical and empirical considerations in the extant literature. In addition, our analysis reveals that outstanding net volumes, a variable at our disposal which has not been used in previous literature, can also exhibit significant explanatory and predictive power on pricing errors. Reductions in net volume can be interpreted as increments of offsetting transactions, which is consistent with a greater number of market participants unwinding positions during periods of distress. The evidence of greater pricing errors in a context of shrinking liquidity is consistent with the theoretical claims in Schleifer and Vishny (1997), since larger price discrepancies can be caused by the temporary exit of market participants. The evidence also agrees with the discussion of Mitchell and Pulvino (2012), who argue that CDS-bond basis distortions during the financial crisis were caused by the trades of investment banks which, being forced to raise cash, massively sold bond positions and unwound related CDS contracts.

The evidence presented in this paper also provides empirical support to the central idea embedded in Hu et al. (2013), namely, that pricing errors are informative of illiquidity conditions. While Treasuries likely provide a more appropriate benchmark to capture illiquidity, the previous results suggest that sovereign CDS prices are partially driven by liquidity-related risk factors. Finally, it should be also noted that the overall evidence reported in this section strongly suggests that single-factor intensity models, specifically intended to capture default risk, may systematically lead to large pricing errors in a distress scenario characterized by high illiquidity risk, as these neglect the influence of this risk-factor. As in the case of the Black-Scholes option pricing model discussed in Peña et al. (1999), extensions of this models that do not accommodate liquidity risk may lead to substantial pricing errors.

5. Robustness checks

This section shows the results from various robustness checks grouped into two main categories that are presented in the next subsections. In Section 5.1, we discuss the general suitability of the model specifications and its estimation when taking into account various considerations. We first analyze if the overall evidence can be extended to both AE and EE, or if there are heterogeneous patterns attending to creditworthiness-related considerations. We also discuss if the estimated models could be improved significantly by adding further variables, or if the results are robust to alternative definitions of the main proxy variables involved in the analysis. Finally, we estimate Model II using multiple instrumentalization through different GMM techniques. In Section 5.2, we analyze whether using alternative pricing models could lead to substantial changes in the main qualitative results discussed previously.

The main conclusion from all this analysis is that the overall evidence discussed previously is robust to all these considerations. For conciseness, we display the results corresponding to Model II, in which the dependent variable is regressed on *Bidask* and ΔX_{it}. The main qualitative conclusions are fairly similar for Model I, but we report the results for a specification that tends to yield more conservative results. All results are available upon request.

5.1. Model specification and econometric estimation

A) Differences between advanced and emerging economies

Paralleling the analysis in section 4.2, Table 6 reports the main outcomes from the panel-data analysis on the subsamples of Emerging Economies (Panel A) and Advanced Economies (Panel B). Before the financial crisis, the global sovereign CDS market was largely focused on emerging countries, characterized by weaker economies and higher default probabilities. Nevertheless, trading activity on CDS contracts on debt obligations from advanced economies, particularly from European countries, increased markedly from the end of 2009. The main aim of this analysis is to determine whether the conclusions discussed previously apply uniformly on both sets of countries.

[INSERT TABLE 6 ABOUT HERE]

The main results show that the bid-ask spread is always positive and strongly significant, independently of the estimation technique, in both groups of countries Hence, local transactions costs and market frictions, captured by bid-ask spreads, prevent arbitrageurs from forcing immediate price convergence and drive pricing errors in both AE and EE areas. The control variable *Default* tends to be marginally significant in the EE group, but not in the AE group, suggesting that it is more difficult for the PS model to accurately capture credit-default driven dynamics in the former. Changes in the number of contracts and *Marketvolatility* are not significant in any group. Finally, the coefficient associated to changes in net volume is negative and remains highly significant, but only in the AE area (see Panel B).

In our view, this result shows important differences in CDS pricing between AE- and EE-related contracts that may be consistent with the fragmentation hypothesis in Goldstein et al. (2013) and/or the existence of clienteles. Fragmentation states that different traders may have heterogeneous motives (e.g., speculative or hedging) when trading in the same market and, therefore, may respond to market shocks in different and even opposite directions. Indeed, sovereign CDS are used essentially for either hedging or speculative purposes. The demand for credit protection is stronger for EE-issued debt because investors, such as large banks and mutual funds, use intensively CDS to hedge long positions in low-rated bonds; see Austin and Miller (2011). On the other hand, professional arbitrageurs and speculators prefer to trade with investment-grade or higher-rated CDS to, for instance, engage in CDS-bond basis strategies; see Austin and Miller (2011), Kim, Li and Zhang (2014) and references therein.[12] The evidence that relative changes in net volume is not significant on the EE group seems to be consistent with the fact that trading activity in this market segment is mainly intended for hedging purposes. Conversely, the evidence that relates significantly greater pricing errors in AE with reductions in net volume may be related to a more intense activity of arbitrageurs and speculators in this part of the market.

In order to gain further insight on the role played by the creditworthiness, we also split the total sample according to the investment- and speculative-grade status of the underlying bonds (we kindly appreciate this suggestion made by a referee). The sample is composed mainly by countries with investment-grade bonds, and only Argentina and Indonesia have speculative-grade bonds. Hence, excluding these countries from this sample does not lead to major differences with respect to the total sample. Finally, we also considered two subsamples formed by AAA to A and BBB to B rated sovereigns in an extension

[12] Among other reasons, holding speculative-grade or lower-rated sovereign debt increases the amount of risk-weighted assets held by the proprietary trading desks of investment banks; see Austin and Miller (2011).

of this analysis, the first group being formed by Australia, China, France, Germany, Japan, Saudi Arabia, South Korea, UK and US, the other, by the remaining countries. The results from this analysis are completely similar to those reported previously, and they are provided in the online Appendix C of the article.

B) Explanatory variables.

Together with the set of variables discussed previously, we included a number of additional explanatory variables in the regression analysis. Most of these variables are global, i.e., variables that are common for all the countries, and that reflect major trends in the global economy. These variables involve *i*) the 1-day LIBOR, since this represents the unsecured rate at which banks lend to each other and hence captures borrowing costs; *ii*) the slope of the US term structure of interest rates, calculated as the difference between the 10- and 2- year constant maturity Treasury bond yields; *iii*) the noise measure of Hu et al. (2013), as a proxy of global illiquidity; *iv*) the local stock market index returns, as a measure of short-term market performance; *v*) the spread between the three-month LIBOR rate and the Overnight Index Swap rates, as a proxy of counterparty risk, since this variable captures the market expectations of future official interest rates set by central banks, and aggregates the perceptions of counterparty risk in credit markets. There exists a strong degree of correlation between these variables. Not surprisingly, therefore, in the estimation of Model I and II extended with these variables, most of the related coefficients were not significant, which suggests that a simpler model that mainly exploits local information is parsimonious enough and subsumes all the relevant information to explain systematic trends in CDS mispricing. The main results, underlining the crucial role played by illiquidity-related variables on price biases, mainly, bid-ask spread, remain unaltered. Finally, whereas certain explanatory variables were significant in Model I, they turned out to be not significant in Model II (e.g., *Contracts*) suggesting that their incremental explanatory power is overriden by the other variables after removing the long-term trend. We estimated Model II without those variables noting no qualitative change in the main conclusions.

C) Financial distress-related deterministic indicators.

We included time dummies signaling the occurrence of major sovereign events in the sample, such as the Greek and Ireland bailouts, and the downgrade of Portugal. The main aim is to isolate the estimates of the main parameters from the influence of these events. To this end, we considered an extended model with dummies in the unconditional mean and cross-effects with all the local variables in our model. The main qualitative results from the analysis do not differ substantially from those discussed previously, suggesting that bid-ask spreads and net volumes are major drivers and even predictors of the noise measure in the sample. Interestingly in this analysis, some variables such as trading activity and default seem to gain statistical significance, with the crossing-effects being particularly significant for the bid-ask spreads, net volumes and default in nearly all model specifications. As a further check, we repeated this exercise by extending the time window effect of the dummies until one, two, three and four weeks after the event, noting that the main qualitative conclusions are essentially the same as those reported previously.

D) Definitions of proxy variables.

We also analyzed the sensitivity of the results to the way in which the main proxy variables have been defined. In particular, the bid-ask is defined as the 5-year maturity bid-ask. This particular choice was motivated by a criterion of homogeneity, since the trading-related variables facilitated by DTCC mainly refer to this maturity. Nevertheless, since bid-ask spreads are available at different maturities, we analyzed the sensitivity of the results to this consideration, considering bid-ask spreads at any of the available maturities, and even the sample average of all of them. Additionally, we consider a different proxy for market-wide volatility in the stock market, using a measure of realized volatility defined as the sum of absolute-valued daily returns over a week. As a further alternative, we also considered the global VIX index (*VIX*) instead of the local volatility proxy. Finally, we measure *Default* alternatively, say *Default2*, as the spread between the High-yield and Investment-grade CDX indexes with 5-year maturity. This may turn into a more accurate measure of the time-varying dynamics of the default-risk premium. Note, furthermore, that either *VIX* or *Default2* can control for time-varying dynamics in risk preferences, thereby ensuring that the main results from our analysis are not driven by considerations related to "reaching for yield" or general appetite for risk. Episodes of increasing appetite for risky assets could be gauged by low levels of *VIX* as well as by the low market risk-premia as measured by *Default2*.[13] The evidence discussed previously is not affected in any significant way by any of these considerations.

[13] We thank an anonymous referee for bringing this point to our attention.

E) Further estimation techniques: GMM estimation

The different specifications discussed previously were characterized using different panel-data estimation techniques. The main purpose was to obtain results robust against different econometric considerations. To deal with potential endogeneity biases, we adopted a simple IV estimation procedure in the panel-data setting using a single lag of the explanatory variables as an instrument. This choice was mainly motivated by methodological convenience. Nevertheless, it seems clear that further lags of the explanatory variables may also constitute valid instruments which may enhance parameter estimation efficiency when used simultaneously. In this subsection, we consider two different approaches that rely on multiple instruments in order to check the robustness of the results discussed in the main section. In particular, we consider different panel data estimation strategies with fixed effects. These procedures not only provide estimates that are robust against heteroskedasticity and autocorrelation, but also against endogeneity by efficiently exploiting the information conveyed by multiple instruments. When using instrumentalization, we noted collinearity-type problems arising from the simultaneous use of *Netvolume* and *Contracts* in Model II.[14] We, therefore, omitted *Contracts* in this analysis, since in Model II this variable tends to add little or no explanatory power in relation to *Netvolume*, as discussed previously, yet it can nevertheless generate statistical distortions under instrumentalization.

In the implementation of panel-data GMM estimation, we first used first-differentiation to remove fixed effects, as in the Arellano and Bond (1991) estimator, and two to four lags of all the explanatory variables as instruments, noting that the J-statistic of Hansen's test cannot reject the overall validity of the moment restrictions implied in this specification. Table 7, Panel A, shows the main statistics (estimates, t-statistics, related p-values, and Hansen's J-statistic) from the GMM estimation of Model II on the total sample and the two AE and EE subsamples. The overall picture that emerges from this analysis is completely similar to that based on the remaining estimation procedures. Bid-ask spread appears clearly as a main determinant of pricing errors, independently of the economic region

[14]Under the multiple-instrument IV panel data estimation considering the total sample, the estimated coefficients related to *Netvolume* and *Contracts* in Model II did not appear to be individually significant but, paradoxically, a standard test for the suitability of the exclusion of both variables from the model led to a strong rejection. This is a clear symptom of collinearity problems between these variables. This is not surprising since it is well-known that multicollinearity problems are exacerbated when using Instrumental Variables; see, among others, Wooldridge (2002).

considered. The variable *Netvol* always has negative coefficients associated and is strongly significant in both the total sample and the subsample of AE countries, but turns out to be non-significant in the EE subsample.

[INSERT TABLE 7 ABOUT HERE]

The Arellano-Bond GMM estimator is distinctively intended for micropanels characterized by a large number of individuals and few time-series observations. In sharp contrast, the panel analyzed in this paper is featured by a moderate number of individuals (16 countries) and a relatively large number of time-series observations (209 weeks). In this context, the large p-value exhibited by the overidentification test may be due to an excessive number of orthogonality conditions given that these grow on the time-series length of the panel and the number of lags used as instruments.[15] This casts logical doubts about the effectiveness of the GMM approach in the context of this paper. To overcome this potential caveat, we additionally implemented a multiple-instrument IV estimator for panel-data with fixed effects in the spirit of the Anderson and Hsiao (1981) estimator. This keeps the total number of orthogonality conditions contained independently of the time-series dimension. As a result, the number of orthogonality conditions equals the number of lags used to instrumentalize the endogenous variables and, consequently, the theory that formally supports the estimator allows for large-sample panels in both the individual and time-series dimensions. As in the Arellano-Bond approach, we implemented this procedure considering two to four lags of the explanatory variables. The main regression outcomes (estimates, t-statistics, related p-values, and Hansen's J-statistic) are presented in Table 7, Panel B. The choice of the number of instruments is formally supported by the overidentification test, with the main results leading to the same basic conclusion discussed previously: While bid-ask spreads appear consistently as a driver of pricing errors, independently of the economic area analyzed, net volumes seem to be mainly related to advanced economies.

5.2. Alternative pricing models

The main results discussed in the previous sections build on the PS pricing model. In order to ensure that the overall discussion is not driven by this particular choice, and since

[15] Alternative procedures to the Arellano-Bond estimator, such as the Arellano and Bover (1995) and Blundell and Bond (1998) estimator, would make this problem even worse as they rely on further orthogonality conditions.

a definitive functional form of the default process $\lambda^{\mathbb{Q}}$ remains an open question in the literature, we consider two alternative pricing models, namely, a quadratic intensity function (QIF) suggested by Houweling and Vorst (2005), and the semi-parametric (NS) model suggested by Nelson and Siegel (1987). Like PS, these alternative approaches rely on CDS spreads to directly measure the credit risk attributable to default risk and do not explicitly accommodate other risk factors, such as liquidity risk. The main methodological difference, however, is that the theoretical term-structure is characterized on cross-sectional estimates at a particular date, whereas PS uses maximum-likelihood in the time-series context. The advantage is that QIF and NS build on flexible semi-parametric specifications that do not impose distributional assumptions on the data. This feature allows us to ensure that the main qualitative conclusions are not driven by the assumptions implied in Pan and Singleton (2008).

The QIF approach builds on a second-order degree polynomial to model the term-structure of the risk-neutral default intensity at maturity m_τ at any time t, namely,

$$\lambda_t^{\mathbb{Q}}(m_\tau) = l_t + s_t m_\tau + c_t m_\tau^2, \tag{15}$$

where the parameters l_t, s_t and c_t capture the level, slope and curvature of the default term structure, respectively, with m_τ denoting the time to maturity, and $\tau = 1, ..., 10$ in our sample. Houweling and Vorst (2005) argue that this approach works reasonably in practice. The main advantage of this specification lies on its methodological tractability, but some readers may deem it as excessively simplistic.

The NS approach is a more sophisticated pricing model that attempts to capture the default spread term structure at time t by parsimoniously fitting a smooth curve to the cross-sectional data, namely,

$$\lambda_t^{\mathbb{Q}}(m_\tau) = \xi_{1t} + \xi_{2t}\frac{1-e^{-\gamma_t m_\tau}}{\gamma_t m_\tau} + \xi_{3t}\frac{1-e^{-\gamma_t m_\tau}}{\gamma_t m_\tau} - \exp\left(-\gamma_t m_\tau\right), \tag{16}$$

where the parameters $(\xi_{1t}, \xi_{2t}, \gamma_t)'$ are latent dynamic factors that admit a precise economic interpretation. In particular, ξ_{1t} can be viewed as the long-term mean of the default intensity; ξ_{2t} is related to the slope of the spread term-structure, since $-\xi_{2t} = \lambda_t^{\mathbb{Q}}(\infty) - \lambda_t^{\mathbb{Q}}(0)$; ξ_{3t} is closely related to the curvature of the shape. Finally, γ_t is related to the convexity of the curve and controls the position, magnitude and direction of the hump of the spread curve. Remarkably, the NS approach provides the corresponding default rate for a continuous of maturities, so additional interpolation is not necessary. Moreover, this modeling approach avoids the over-parametrization, allowing for monotonically increasing or decreasing and hump shaped default term curves. Jankowitsch, Pullirsch and Veza (2008) set an extensive comparison of the pricing properties in the bond market for several parametrizations of the default intensity, concluding that the Nelson and Siegel (1987) specification turned out to be optimal.

Recalling that the (annualized) price of a CDS contract for maturity m at time t obeys (6), we can use the following discretized version of this formula for computing the spreads under both the QIF and NS approaches,

$$\frac{1}{4}\sum_{j=1}^{4m} e^{-\frac{j}{4}\left(r_t+\lambda_t^{\mathbb{Q}}(j)\right)} CDS_t(m) = (1-\mathbb{R}^{\mathbb{Q}}) \sum_{j=1}^{4m} e^{-\frac{j}{4}r_t}\left[e^{-\frac{(j-1)}{4}\lambda_t^{\mathbb{Q}}(j)} - e^{-\frac{j}{4}\lambda_t^{\mathbb{Q}}(j)}\right], \qquad (17)$$

where $\lambda_t^{\mathbb{Q}}(j)$ denotes the risk-neutral default intensity at maturity j, and $\mathbb{R}^{\mathbb{Q}}$ is the recovery rate. Consistent with previous literature, we set the risk-neutral recovery rate to 40%. We also assume a constant default intensity $\lambda_t^{\mathbb{Q}}$, which results in $CDS_t^*(m_\tau) \approx \lambda_t^{\mathbb{Q}}(m_\tau)(1-\mathbb{R}^{\mathbb{Q}})$. The parameters $(l_t, s_t, c_t)'$ and $(\xi_{1t}, \xi_{2t}, \xi_{3t}, \gamma_t)'$ that characterize the QIF and NS models are estimated using linear and non-linear least squares, respectively, given the observable curve CDS_t; see, for instance, Houweling and Vorst (2005). Since γ_t in the NS model should be positive in order to assure convergence to the long-term value ξ_{1t}, we impose the constraints $\xi_{1t} > 0$, $\xi_{1t} + \xi_{2t} > 0$ and $\gamma_t > 0$ in the numerical optimization of the objective loss-function of this model. Given the resultant estimates, it is straightforward to compute theoretical term-structure CDS prices and, hence, determine the noise measure with respect to the observed prices CDS_t.

Figure 2 shows the time series of the cross-country median of the theoretical CDS spreads implied by the three different pricing models considered in this paper. For comparative purposes, the figure also reports the qq-plots of these series in logarithms. Clearly, all these model-implied CDS spreads tend to exhibit similar time series features on average. The pairwise correlation between the model-implied prices from PS and those from QIF and NS are about 76% and 74%, respectively. Similarly, the correlation between the theoretical prices generated with the QIF and NS models is nearly 80%. Note that the CDS spreads implied by PS and NS have a similar level and tend to overlap, but the latter display a considerably degree of additional volatility. Theoretical prices from the QIF model exhibit similar time series properties as the other two methodologies, but the average is downward shifted, i.e., prices are systematically smaller.

[INSERT FIGURE 2 ABOUT HERE]

Table 8 reports the main results from the analysis of determinants of the QIF- and NS-based noise measures. For ease of exposition, we report the estimates of Table 8 noting that the dependent variable $\ln noise_{CDS,it}$ is now computed according to the residuals of either the QIF or the NS models. Not surprisingly in view of the strong correlation between the theoretical prices generated by these pricing methodologies, the overall picture that emerges is fully consistent with the main qualitative evidence discussed in Section 4.2.[16] The main conclusion from this analysis, therefore, is that the overall evidence that pricing errors from default single-factor models can be consistently related to market-wide illiquidity variables is not driven by the particular choice of the theoretical pricing model and holds generally when using different approaches.

[INSERT TABLE 8 ABOUT HERE]

6. Concluding remarks

The term structure of fixed-income derivative products must be consistently priced across maturities under the absence of arbitrage opportunities. In practice, however, temporary discrepancies between observed prices and theoretical values can arise as a consequence of market frictions and, more generally, market illiquidity. While the extant literature has documented both theoretically and empirically the unmitigated influence of illiquidity-related costs on arbitrage-free option pricing models, the evidence for other derivative markets is generally scarce, and plainly nonexistent for CDS. The main objective of this paper has been to contribute to this literature by documenting the existence of systematic illiquidity-related patterns in the pricing errors implied by some of the most popular pricing models used to value CDS spreads. To this end, we have implemented different panel-data estimation techniques on a broad sample of sovereign CDS in 16 countries.

[16] The only meaningful difference in the qualitative conclusions refers to the significance of the control variable *Default*, which is positive and statistically significant under the QIF model. This means that such model may not succeed in capturing the embedded default risk in CDS spreads.

The main evidence in this paper is remarkably robust and suggests that price discrepancies in CDS markets can systematically be related to illiquidity factors. Pricing errors tend to be greater during periods of significant distress, such as the collapse of Lehman Brothers or the European debt crisis, as expected under the general arbitrage capital hypothesis. Bid-ask spread is identified in the panel-data analysis as a key economic determinant, and even as a reliable short-term predictor, of price divergences. Increasing offsetting transactions can also be related to large pricing errors both in determinant and predictive regressions, particularly, in the group of advanced economies. The overall evidence presented and discussed in this paper is largely consistent with the hypothesis that arbitrage capital is affected by market conditions and exits the market during times of distress, causing assets to be traded at prices significantly different to their fundamental value. Accordingly, theoretical pricing models that fail to properly accommodate the additional compensation required for market maker risks can systematically lead to pricing errors in this context.

This evidence is important for different agents, including investors who trade in the sovereign CDS market and supervisory organisms that use sovereign CDS transaction prices as reliable indicators of the underlying economic conditions. On the one hand, most investors trade in CDS markets for either speculative or hedging purposes. For both types of agents, the evidence that state-of-the-art CDS pricing models can generate prices that systematically depart from real prices is particularly relevant for its economic implications. Investment decisions based on the theoretical prices generated by these models may lead to suboptimal results in a distress scenario. On the other hand, regulators and supervisory organisms often closely monitor financial and economic time series looking for signals that may anticipate a financial weakening. The sovereign CDS market provides natural indicators for this end, since CDS spreads convey information on market expectations of creditworthiness. However, if sovereign CDS spreads are wrongly assumed to solely reflect default risk, the severity of the underlying market conditions could be largely overestimated, particularly, during periods of distress. In this context, transaction prices may no longer reflect fundamental values, but also include large illiquidity-risk premiums, as directly suggested by the recent literature on the field, and confirmed from the empirical findings in this paper. The case of peripheral European countries in the midst of the European sovereign crisis perhaps illustrates this point accurately, since sovereign CDS contracts were traded at excessively high prices to solely reflect credit default risk premia.

The results from this paper are drawn from an empirical analysis focused exclusively on sovereign CDS data, which poses logical limitations to the generality of main conclusions involved. An interesting topic for further research, consequently, is the extension of this analysis to the corporate segment of the derivative credit market. The motivation for analyzing illiquidity-related frictions is much more prevalent in the corporate CDS market given the difficulties to short-sell illiquid bonds and the associate effects on CDS-bond basis and arbitrage. Furthermore, such a study would be of interest because it would allow to address additional questions more precisely and which cannot be explored in our study owing to limitations in the dataset. In this regard, it seems of particular interest to formally characterize clientele-type effects related to investment-grade and high-yield segments of the corporate market using more detailed information. The evidence reported in the current paper provides clear insight on the relations that should be expected, but a formal analysis on this question constitutes an interesting topic for future research.

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Table 1: Maximum likelihood estimates

Country	$\kappa^{\mathbb{Q}}$	$\kappa^{\mathbb{Q}}\theta^{\mathbb{Q}}$	σ	$\kappa^{\mathbb{P}}$	$\kappa^{\mathbb{P}}\theta^{\mathbb{P}}$	σ_G	$R^{\mathbb{Q}}$	LogLk
Argentina	0.0977	-0.3111	1.1515	0.4100	-1.3947	0.0158	0.0100	10055.49
	(0.0109)	(0.0345)	(0.0054)	(0.4271)	(1.4933)	(0.0000)	(0.0032)	
Australia	-0.1576	0.5665	0.8519	2.0488	-9.7753	0.0006	0.6568	14361.35
	(0.0055)	(0.0253)	(0.0086)	(1.0181)	(4.9049)	(0.0000)	(0.0246)	
Brazil	-0.0372	0.3160	0.9967	1.4271	-6.0946	0.0015	0.7120	18082.42
	(0.0046)	(0.0235)	(0.0058)	(0.5463)	(2.2478)	(0.0000)	(0.0065)	
China	-0.0725	0.2836	1.0452	0.6028	-3.2016	0.0010	0.6741	19873.02
	(0.0051)	(0.0270)	(0.0048)	(0.5508)	(2.7026)	(0.0000)	(0.0124)	
France	-0.3077	1.2479	0.7489	0.7476	-3.9226	0.0008	0.7792	20549.94
	(0.0044)	(0.0180)	(0.0026)	(0.2650)	(1.4954)	(0.0000)	(0.0050)	
Germany	-0.3294	1.4366	0.7977	0.3122	-1.8284	0.0006	0.7966	21590.77
	(0.0049)	(0.0226)	(0.0046)	(0.4622)	(2.6673)	(0.0000)	(0.0075)	
Indonesia	0.0262	-0.0780	1.0802	0.8218	-3.6363	0.0026	0.3690	16292.05
	(0.0029)	(0.0152)	(0.0064)	(0.5350)	(2.2836)	(0.0000)	(0.0129)	
Italy	-0.1439	0.4858	0.8729	0.0935	-0.3948	0.0016	0.7069	18222.76
	(0.0065)	(0.0231)	(0.0044)	(0.3268)	(1.2389)	(0.0000)	(0.0049)	
Japan	-0.2444	1.0591	1.0024	0.6477	-3.9007	0.0008	0.4715	20608.46
	(0.0037)	(0.0181)	(0.0060)	(0.5088)	(3.3369)	(0.0000)	(0.0139)	
Mexico	-0.0637	0.3664	0.9337	0.1722	-0.8381	0.0009	0.7454	19782.02
	(0.0031)	(0.0140)	(0.0050)	(0.3099)	(1.2314)	(0.0000)	(0.0030)	
Saudi Arabia	-0.1952	0.6712	0.6739	0.9137	-3.8040	0.0007	0.5927	13230.57
	(0.0027)	(0.0093)	(0.0068)	(1.0620)	(4.2584)	(0.0000)	(0.0124)	
South Africa	0.2871	-1.2749	1.9191	0.5267	-2.9677	0.0012	0.7046	18922.40
	(0.0061)	(0.0393)	(0.0076)	(0.5213)	(2.6152)	(0.0000)	(0.0061)	
South Korea	-0.0087	0.1557	0.8793	0.3607	-1.6318	0.0011	0.8246	19178.13
	(0.0017)	(0.0066)	(0.0019)	(0.2136)	(0.7573)	(0.0000)	(0.0015)	
Spain	-0.0720	0.0833	0.8929	0.1361	-0.8052	0.0014	0.0335	18550.07
	(0.0018)	(0.0063)	(0.0039)	(0.1944)	(1.1928)	(0.0000)	(0.0066)	
UK	0.2227	-1.2409	1.7872	0.4324	-2.8469	0.0008	0.7695	14987.91
	(0.0236)	(0.1769)	(0.0105)	(0.8604)	(4.8489)	(0.0000)	(0.0350)	
US	0.0176	-0.1397	0.8465	0.2009	-1.1237	0.0005	0.7390	15755.24
	(0.0028)	(0.0151)	(0.0047)	(0.3980)	(2.1537)	(0.0000)	(0.0138)	

Maximum likelihood estimates of the PS model (robust standard errors in parenthesis). The parameters $\kappa^{\mathbb{Q}}$, $\theta^{\mathbb{Q}}$, and $\sigma^{\mathbb{Q}}$ denote the mean-reversion, long-run mean and instantaneous volatility of default intensity process $\lambda^{\mathbb{Q}}$ under the risk-neutral probability measure, respectively. Similar convention applies for the parameters of the objective measure ($\mathbb{P}$). The parameter σ_M is the standard deviation of mispricing errors, and $R^{\mathbb{Q}}$ denotes the recovery rate. LogLk is the value of log-likelihood function. Data frequency is weekly and comprises from January 2006 to November 2012, with the exception of Saudi Arabia, UK and US, which covers from December 2007 to November 2012.

Table 2: Descriptive statistics of the noise measure in sovereign CDS contracts

Country	Mean	Median	Std	Min	Max	Percentiles 5%	Percentiles 95%	Obs.
Argentina	85.70	43.87	136.40	4.41	1111.39	7.84	472.10	358
Australia	4.42	2.66	4.67	0.33	21.44	1.28	17.47	244
Brazil	12.11	10.78	9.46	1.06	57.31	2.54	32.18	358
China	7.44	4.96	6.10	0.40	27.90	1.22	18.76	358
France	5.80	3.80	5.89	0.42	28.09	1.18	19.51	358
Germany	4.52	3.11	4.37	0.37	18.75	0.61	15.08	358
Indonesia	17.79	12.47	19.06	1.39	219.45	4.77	59.08	358
Italy	11.37	5.85	11.13	1.62	66.65	2.88	59.08	358
Japan	5.80	4.66	4.91	0.41	26.19	0.82	15.18	358
Mexico	7.87	6.68	4.93	1.49	56.84	2.36	16.25	358
Saudi Arabia	5.58	4.92	3.91	0.85	18.24	1.05	14.62	228
South Africa	9.91	7.90	7.01	2.02	56.34	3.01	21.92	358
South Korea	9.48	7.80	6.45	2.21	43.66	2.97	21.58	358
Spain	10.11	6.33	10.19	1.09	62.43	1.60	30.39	358
UK	6.84	5.33	3.83	1.40	17.75	2.52	13.65	261
US	4.57	3.87	2.73	0.53	17.22	1.12	10.52	257

Main descriptive statistics of the noise measure (in basis points) computed from the PS model in sovereign CDS spreads for each country. Sample period comprises from January 2006 to November 2012, with the exception of Australia, Saudi Arabia, UK and US, which covers from December 2007 to November 2012. Data frequency is weekly.

Table 3: Relative (%) contribution of each maturity to the noise measure

	Maturity (years)									Top ranking	
Country	1	2	3	4	6	7	8	9	10	mean	median
Argentina	59.20	39.44	26.28	12.86	9.63	16.62	20.82	23.33	25.03	1	1
	[64.57]	[43.48]	[25.96]	[10.96]	[8.29]	[14.41]	[19.09]	[21.70]	[22.06]		
Australia	32.54	33.99	29.68	18.34	19.84	29.79	35.43	35.42	36.84	10	8
	[30.35]	[36.81]	[31.98]	[18.85]	[22.82]	[33.45]	[40.18]	[38.99]	[38.73]		
Brazil	45.51	38.02	29.17	19.19	12.34	23.07	27.54	31.48	34.65	1	1
	[46.10]	[39.11]	[29.16]	[18.09]	[12.82]	[23.98]	[30.13]	[34.35]	[37.58]		
China	32.38	30.05	26.99	14.22	13.20	25.63	32.53	39.17	43.48	10	10
	[34.97]	[31.72]	[25.91]	[14.35]	[13.62]	[25.53]	[34.76]	[42.11]	[42.66]		
France	51.69	38.86	26.43	14.83	12.67	21.10	26.06	29.84	33.23	1	1
	[56.95]	[40.00]	[26.19]	[15.18]	[12.14]	[20.01]	[25.56]	[30.26]	[34.31]		
Germany	49.90	34.25	27.66	16.30	13.11	20.94	26.09	30.20	34.33	1	1
	[48.16]	[36.11]	[27.80]	[16.30]	[11.94]	[20.13]	[27.57]	[31.35]	[36.45]		
Indonesia	49.28	39.09	32.23	16.00	11.43	19.19	23.36	27.70	33.67	1	1
	[52.52]	[42.88]	[33.74]	[15.08]	[10.67]	[18.37]	[24.69]	[29.56]	[35.59]		
Italy	56.68	38.35	23.07	10.55	9.94	15.84	20.30	25.74	31.62	1	1
	[62.50]	[40.10]	[20.12]	[9.43]	[9.05]	[15.53]	[17.83]	[19.83]	[25.89]		
Japan	50.76	31.10	23.50	15.25	13.70	20.94	26.14	30.73	36.03	1	1
	[51.81]	[32.09]	[24.07]	[14.62]	[12.44]	[20.40]	[27.52]	[33.80]	[39.31]		
Mexico	54.74	31.38	22.05	12.71	10.24	18.80	24.04	29.20	37.42	1	1
	[60.15]	[33.05]	[20.11]	[12.02]	[10.10]	[17.59]	[24.48]	[29.36]	[39.57]		
Saudi Arabia	45.83	42.25	29.08	14.18	14.26	21.43	23.37	23.34	26.08	1	2
	[49.00]	[51.60]	[30.30]	[14.85]	[11.00]	[8.74]	[15.14]	[23.76]	[30.92]		
South Africa	51.74	43.14	28.56	12.90	10.93	18.72	23.76	27.86	32.05	1	1
	[53.49]	[44.69]	[29.00]	[12.43]	[10.94]	[18.02]	[24.78]	[29.52]	[32.61]		
South Korea	42.58	33.18	24.65	13.73	11.50	21.41	28.55	34.73	39.56	1	1
	[46.70]	[38.94]	[23.62]	[10.74]	[11.11]	[20.69]	[27.83]	[33.22]	[35.31]		
Spain	53.61	38.12	26.17	13.42	11.38	17.79	22.64	26.79	32.24	1	1
	[53.09]	[35.18]	[26.45]	[11.47]	[10.33]	[18.63]	[21.77]	[25.95]	[28.97]		
UK	44.92	43.73	36.82	17.47	12.07	19.81	24.12	26.39	27.64	1	2
	[43.98]	[50.74]	[35.30]	[15.47]	[11.30]	[18.64]	[22.98]	[26.30]	[27.88]		
US	26.93	32.76	26.99	13.86	12.71	22.44	32.78	41.59	48.62	10	10
	[22.47]	[32.93]	[26.16]	[14.21]	[13.68]	[25.36]	[35.99]	[45.79]	[53.52]		

Main descriptive statistics for the relative contribution (in percentage) of different maturities to the noise measure computed from the PS model: Mean and median (in brackets). The relative contribution of the 5-year maturity is zero by construction and, hence, omitted. The final columns show the top maturity contributor according to the average and medians.

Table 4: OLS regressions of the first principal component of the noise measure

Constant	ΔVIX	ΔDefault	Market Return	ΔPC1netvol	ΔPC1BA5y	Adj-R^2	Obs.
0.0397	0.0616***					18.20	227
(0.0353)	(0.0086)						
0.0413		1.8627***				5.00	227
(0.0381)		(0.5188)					
0.0415			-0.0027***			21.79	227
(0.0346)			(0.0003)				
0.0426				-0.4468		1.38	185
(0.0410)				(0.2366)			
0.0371					-0.2316***	10.99	227
(0.0369)					(0.0431)		
0.0633	0.0366*	-0.0273	-0.0016*	-0.4358*	-0.1173	25.75	185
(0.0364)	(0.0183)	(0.7145)	(0.0007)	(0.2107)	(0.0778)		

OLS estimates (Newey-West standard errors in parenthesis) of the increments of the first principal component of the PS-based noise measure (ΔPC1) on the explanatory variables in columns. Last columns show the adjusted R-squared statistic and the number of observations in each regression. Total sample period spans from July 2008 to November 2012. Statistical significance is indicated as follows: $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Table 5: Panel-data and predictive analysis of CDS price discrepancies

	Two-way cluster			**Panel-data Fixed-Effects**			**Instrumental Fixed Effects**			**Predictive Two-way cluster**		
	Estimate	Est. Error	*p*-value	Estimate	Est. Error	*p*-value	Estimate	Est. Error	*p*-value	Estimate	Est. Error	*p*-value
Panel A.- Model I												
logBidaskspread5Y	0.5251	0.0766	0.00	0.5251	0.0718	0.00	0.5330	0.0318	0.00	0.5104	0.0842	0.00
logContracts	0.5780	0.1596	0.00	0.5780	0.1554	0.00	0.5650	0.0417	0.00	0.5593	0.1598	0.00
logNetvolume	-0.3193	0.1338	0.02	-0.3193	0.1325	0.03	-0.2970	0.0522	0.00	-0.2823	0.1296	0.03
Marketvolatility	0.7383	0.4554	0.11	0.7383	0.3617	0.06	0.7372	0.4698	0.12	0.1310	0.2811	0.64
Default	0.1223	0.1044	0.24	0.1222	0.0990	0.24	0.1338	0.0276	0.00	0.1477	0.1067	0.17
Constant	-5.4617	2.4059	0.02	-4.9798	2.3723	0.05	-5.4003	0.8978	0.00	-6.1473	2.2953	0.01
Country Dummies	Yes	Yes	Yes	No	No	No	No	No	No	Yes	Yes	Yes
Observations	3131	3131	3131	3131	3131	3131	3101	3101	3101	3101	3101	3101
R^2-coefficient	0.9418	0.9418	0.9418	0.9418	0.9418	0.9418	-	-	-	0.9417	0.9417	0.9417

	Estimate	Est. Error	*p*-value	Estimate	Est. Error	*p*-value	Estimate	Est. Error	*p*-value	Estimate	Est. Error	*p*-value
Panel B.- Model II												
logBidaskspread5Y	0.5740	0.0611	0.00	0.5740	0.0587	0.00	0.5835	0.0207	0.00	0.5604	0.0612	0.00
ΔlogContracts	-0.2468	0.3914	0.53	-0.2468	0.3522	0.49	-0.2549	0.3100	0.41	-0.2123	0.3634	0.56
ΔlogNetvolume	-0.8498	0.5392	0.12	-0.8498	0.4878	0.10	-0.9074	0.3436	0.01	-1.0404	0.5328	0.05
ΔMarketvolatility	0.2862	0.3600	0.43	0.2862	0.2764	0.32	0.2153	0.3742	0.57	0.0917	0.2950	0.76
ΔDefault	-0.2199	0.4621	0.63	-0.2199	0.3897	0.58	-0.0563	0.1950	0.77	-0.2178	0.4554	0.63
Constant	-8.6457	0.1042	0.00	-7.3340	0.0961	0.00	-7.3464	0.0347	0.00	-8.6218	0.1051	0.00
Country Dummies	Yes	Yes	Yes	No	No	No	No	No	No	Yes	Yes	Yes
Observations	3115	3115	3115	3115	3115	3115	3099	3099	3099	3099	3099	3099
R^2-coefficient	0.9355	0.9355	0.9355	0.9355	0.9355	0.9355	-	-	-	0.9349	0.9349	0.9349

Panel-data estimates of Model I and II using different estimation procedures. The dependent variable in all cases is the log-transform of the PS-based noise measure. This is regressed on (log) bid-ask spreads, and on the remaining variables by rows expressed either in levels (Panel A) or in differences (Panel B). By columns, the first set of results shows estimates, robust standard errors and related p-values from a pooled time-series cross-sectional regression with two-way cluster-robust standard errors accounting for country and week clusters. The second set reports statistics from a panel-data regression with fixed effects. The third set shows the estimates of IV panel-data estimation using a single lag of the explanatory variables as instrument. Finally, the last set of columns shows the results from a predictive regression (all explanatory variables are lagged one period) using pooled time-series cross-sectional regressions with two-way cluster-robust standard errors accounting for country and week clusters.

Table 6: Panel-data determinants and predictive analysis of CDS price discrepancies across economic groups

	Two-way cluster			**Panel-data Fixed-Effects**			**Instrumental Fixed Effects**			**Predictive Two-way cluster**		
	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value
Panel A.- EE Group												
logBidaskspread5Y	0.6416	0.0507	0.00	0.6416	0.0489	0.00	0.6467	0.0239	0.00	0.6218	0.0564	0.00
ΔlogContracts	0.3284	0.6903	0.63	0.3284	0.7094	0.66	0.3184	0.4928	0.52	0.0445	0.6934	0.95
ΔlogNetvolume	0.1331	0.5286	0.80	0.1331	0.5253	0.81	0.1501	0.4365	0.73	-0.0350	0.4765	0.94
ΔMarketvolatility	0.5541	0.3534	0.12	0.5541	0.3433	0.15	0.4677	0.4836	0.33	0.0962	0.2813	0.73
ΔDefault	-0.9532	0.4837	0.05	-0.9532	0.4734	0.08	-0.8947	0.2665	0.10	-0.8658	0.5152	0.09
Constant	-7.9771	0.0509	0.00	-6.5870	0.0881	0.00	-6.5979	0.0438	0.00	-7.9609	0.0579	0.00
Country Dummies	Yes	Yes	Yes	No	No	No	No	No	No	Yes	Yes	Yes
Observations	1482	1482	1482	1482	1482	1482	1474	1474	1474	1474	1474	1474
R^2-coefficient	0.9658	0.9658	0.9658	0.9658	0.9658	0.9658	-	-	-	0.9651	0.9651	0.9651
	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value
Panel B.- AE Group												
logBidaskspread5Y	0.4221	0.1103	0.00	0.4221	0.1034	0.01	0.4367	0.0378	0.00	0.4221	0.1082	0.00
ΔlogContracts	-0.2773	0.4491	0.54	-0.2773	0.3619	0.47	-0.2589	0.4047	0.52	-0.0834	0.3974	0.83
ΔlogNetvolume	-1.8605	0.8315	0.03	-1.8605	0.7169	0.04	-2.0425	0.5312	0.00	-2.1216	0.7097	0.00
ΔMarketvolatility	0.0004	0.6135	1.00	0.0004	0.4051	1.00	-0.0644	0.5644	0.91	0.0881	0.5208	0.87
ΔDefault	0.5519	0.6724	0.41	0.5519	0.5276	0.33	0.8290	0.2797	0.00	0.4654	0.6965	0.50
Constant	-8.3786	0.1808	0.00	-7.8933	0.1504	0.00	-7.9065	0.0574	0.00	-8.3794	0.1770	0.00
Country Dummies	Yes	Yes	Yes	No	No	No	No	No	No	Yes	Yes	Yes
Observations	1633	1633	1633	1633	1633	1633	1625	1625	1625	1625	1625	1625
R^2-coefficient	0.3349	0.3349	0.3349	0.3349	0.3349	0.3349	-	-	-	0.3437	0.3437	0.3437

Panel-data estimates of Model I and II using different estimation procedures and considering subsamples of Emerging economies (EE) and Advanced Economies (AE); see caption of Table 5 for details on estimation procedures. Advanced economies in our sample are formed by Australia, France, Germany, Italy, Japan, Spain, UK, and US. Emerging economies are formed by the remaining countries in the sample.

Table 7: GMM panel-data determinants and predictive analysis of CDS price discrepancies across different samples

	All sample			**AE sample**			**EE sample**		
	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value
	Panel A.- Model II Arellano-Bond approach								
logBidaskspread5Y	0.4455	0.0686	0.00	0.4208	0.0969	0.00	0.5661	0.0714	0.00
ΔlogNetvolume	-0.5609	0.3389	0.10	-1.9541	0.6788	0.00	-0.0857	0.4289	0.84
ΔMarketvolatility	0.3279	0.2207	0.14	-0.0079	0.4009	0.98	0.5707	0.3115	0.07
ΔDefault	-0.3147	0.2222	0.16	0.5556	0.4935	0.26	-0.6942	0.2653	0.01
Hansen's J-test	12.52 (0.99)			4.53 (0.99)			4.93 (0.99)		
	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value
	Panel B.- Model II Anderson-Hsiao approach								
logBidaskspread5Y	0.6233	0.0368	0.00	0.7421	0.2992	0.01	0.6402	0.0443	0.00
ΔlogNetvolume	-7.9784	3.3013	0.02	-12.0025	3.2531	0.00	-0.7142	4.3132	0.87
ΔMarketvolatility	4.7828	5.5725	0.39	2.6735	5.8811	0.65	0.9104	6.9536	0.90
ΔDefault	-0.0169	0.5613	0.98	1.6417	0.7861	0.04	2.4398	0.7567	0.00
Constant	-7.3812	0.0650	0.00	-8.2788	0.4405	0.00	-6.6133	0.0812	0.00
Hansen's J-test	6.21 (0.62)			10.8 (0.21)			6.86 (0.55)		

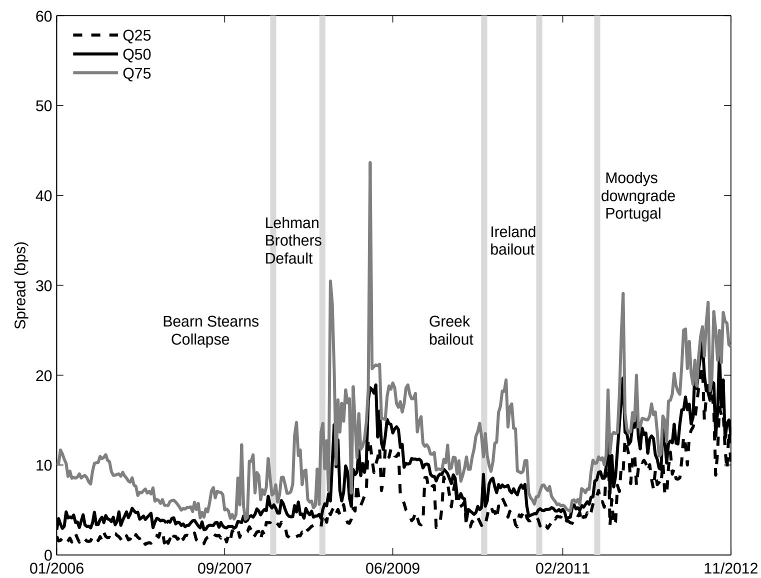
Panel data estimates for noise measure using different GMM procedures. The mispricing errors have been computed using Pan and Singleton (2008) model. Panel A shows the results for variables in differences using GMM from Arellano and Bond procedure. Panel B depicts the results for variables in differences using IV fixed effects in the spirit of Anderson-Hsiao estimator. First column corresponds with regressions for all sample. Second column shows the results for advanced economies. The last column presents the estimation for emergent group. Finally, this table reports the test and p-values of Hansen's test. This test checks the joint validity of the instruments employed in the estimation.

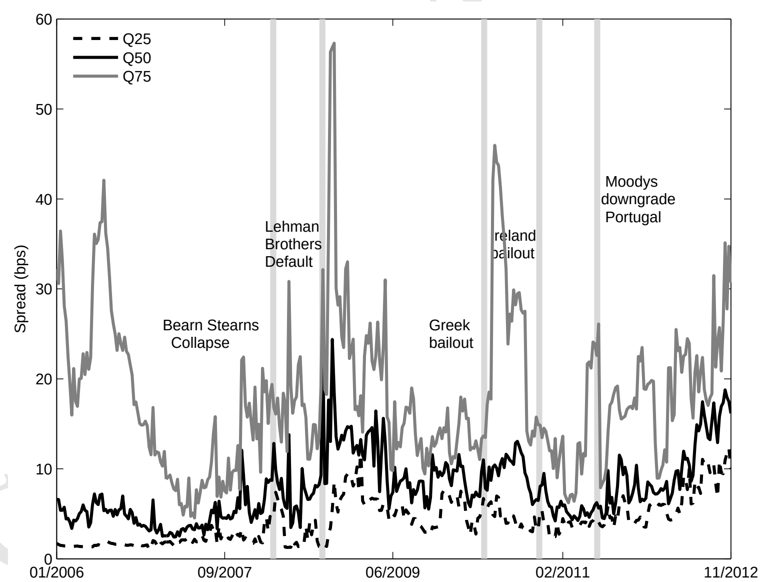
Table 8: Panel-data determinants and predictive analysis of CDS price discrepancies from different pricing models

	Two-way cluster			Panel data Fixed Effects			Instrumental Fixed Effects			Predictive Two-way cluster		
	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value
Panel A.- QIF Model												
logBidaskspread5Y	0.3695	0.1049	0.00	0.3793	0.1005	0.00	0.3863	0.0233	0.00	0.3471	0.1015	0.00
ΔlogContracts	0.2102	0.9473	0.82	0.1503	0.4234	0.72	0.0009	0.7996	0.99	-0.2421	1.1060	0.83
ΔlogNetvolume	-2.9275	1.3588	0.03	-2.9305	1.2655	0.02	-3.0072	0.8787	0.00	-2.6033	1.2017	0.03
ΔMarketvolatility	0.2438	0.4459	0.58	0.2440	0.1639	0.14	0.2848	0.4204	0.50	0.1338	0.4581	0.77
ΔDefault	1.2566	0.5448	0.02	1.2603	0.3937	0.00	1.5150	0.2191	0.00	1.1011	0.5106	0.03
Constant	-9.8490	0.1759	0.00	-9.0103	0.2426	0.00	-8.9705	0.0389	0.00	2.7646	0.1597	0.00
Country Dummies	Yes	Yes	Yes	No	No	No	No	No	No	Yes	Yes	Yes
Observations	3168	3168	3168	3168	3168	3168	3152	3152	3152	3152	3152	3152
R^2-coefficient	0.6218	0.6218	0.6218	0.6218	0.6218	0.6218	-	-	-	0.6178	0.6178	0.6178
	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value
Panel B.- NS Model												
logBidaskspread5Y	0.1550	0.0916	0.09	0.1634	0.0933	0.08	0.1659	0.0231	0.00	0.1446	0.0922	0.12
ΔlogContracts	-0.1028	0.8326	0.90	-0.1247	0.7723	0.87	-0.2073	0.7914	0.79	-0.0557	0.8174	0.95
ΔlogNetvolume	-2.4881	1.0928	0.02	-2.4662	1.0574	0.02	-2.4301	0.8697	0.01	-1.9586	0.9333	0.04
ΔMarketvolatility	-0.0499	0.3436	0.88	-0.0499	0.2936	0.87	-0.0715	0.4161	0.86	0.0746	0.3060	0.81
ΔDefault	0.4474	0.3876	0.25	0.4438	0.3069	0.15	0.5519	0.2168	0.01	0.5448	0.3800	0.15
Constant	-8.5070	0.1573	0.00	-8.0439	0.1640	0.00	-8.0039	0.0385	0.00	-8.4916	0.1563	0.00
Country Dummies	Yes	Yes	Yes	No	No	No	No	No	No	Yes	Yes	Yes
Observations	3168	3168	3168	3168	3168	3168	3152	3152	3152	3152	3152	3152
R^2-coefficient	0.2651	0.2651	0.2651	0.2651	0.2651	0.2651	0.2631	0.2631	0.2631	0.2631	0.2631	0.2631

Panel-data estimates of Model II using different estimation procedures (see caption to Table 5 for details) with the noise measure being generated under alternative pricing models, namely, a quadratic intensity model suggested by Houweling and Vorst (2005) (Panel A) and the Nelson-Siegel model (Panel B).

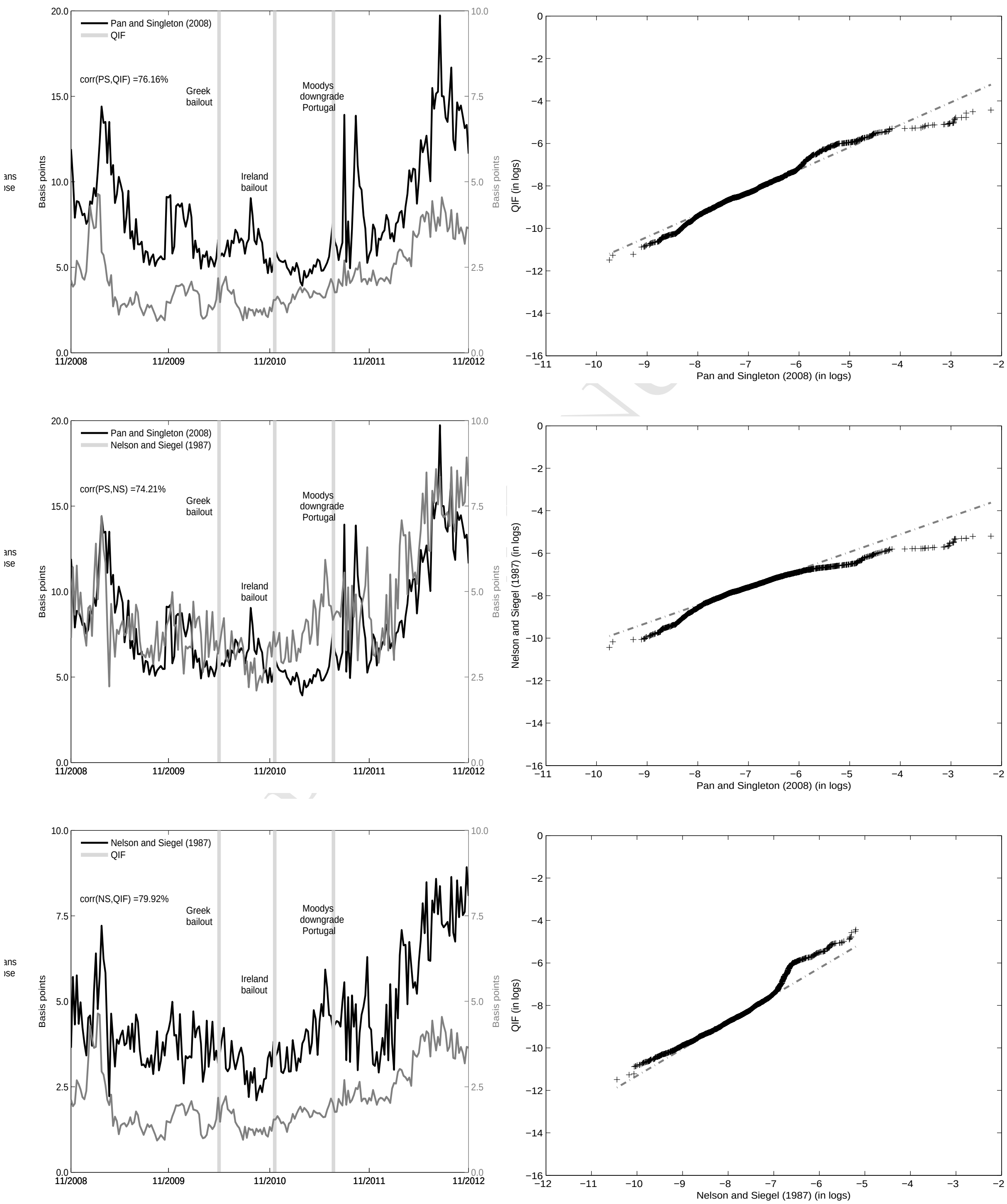
Figure 1: Time-series dynamics of price discrepancies in sovereign CDS contracts



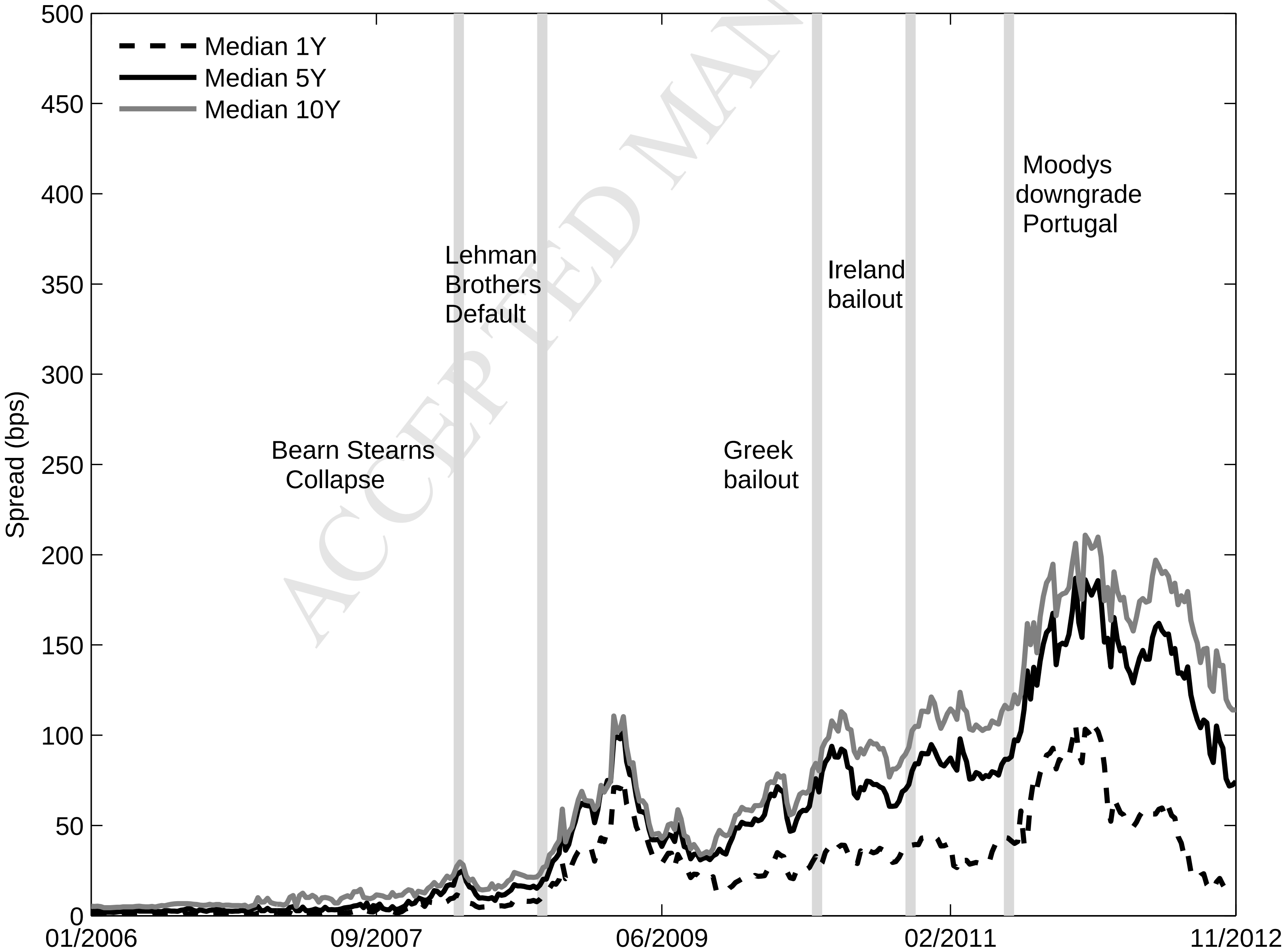


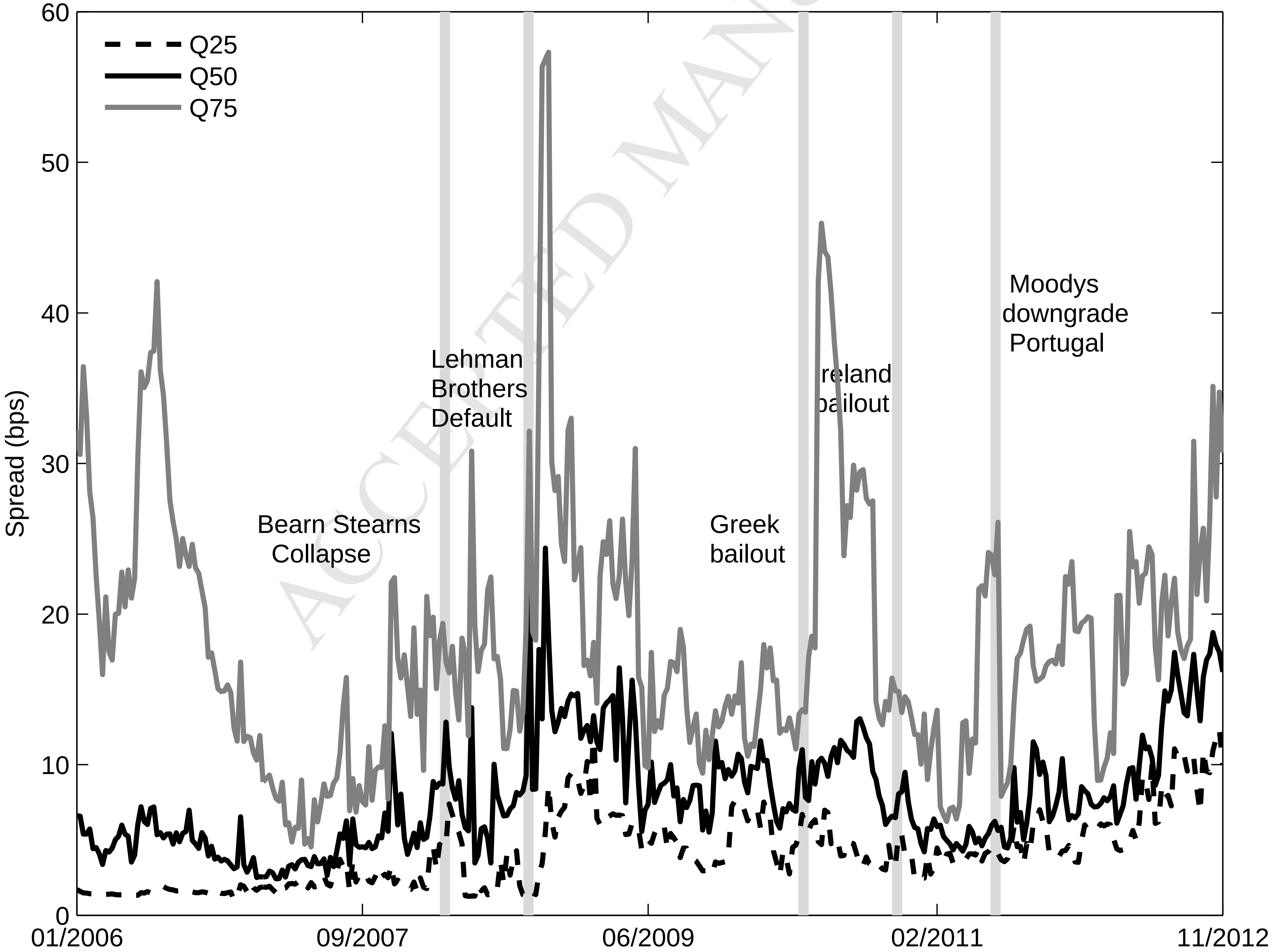
This Figure displays the evolution of different percentiles of the noise measure using Pan and Singleton (2008) model as pricing model. The noise measure is computed for advanced (upper graph) and emerging (lower graph) economies. Advanced countries comprise Australia, France, Germany, Italy, Japan, Spain, the United Kingdom and the US. The sample period spans from January 2006 to November 2012. Data frequency is weekly.

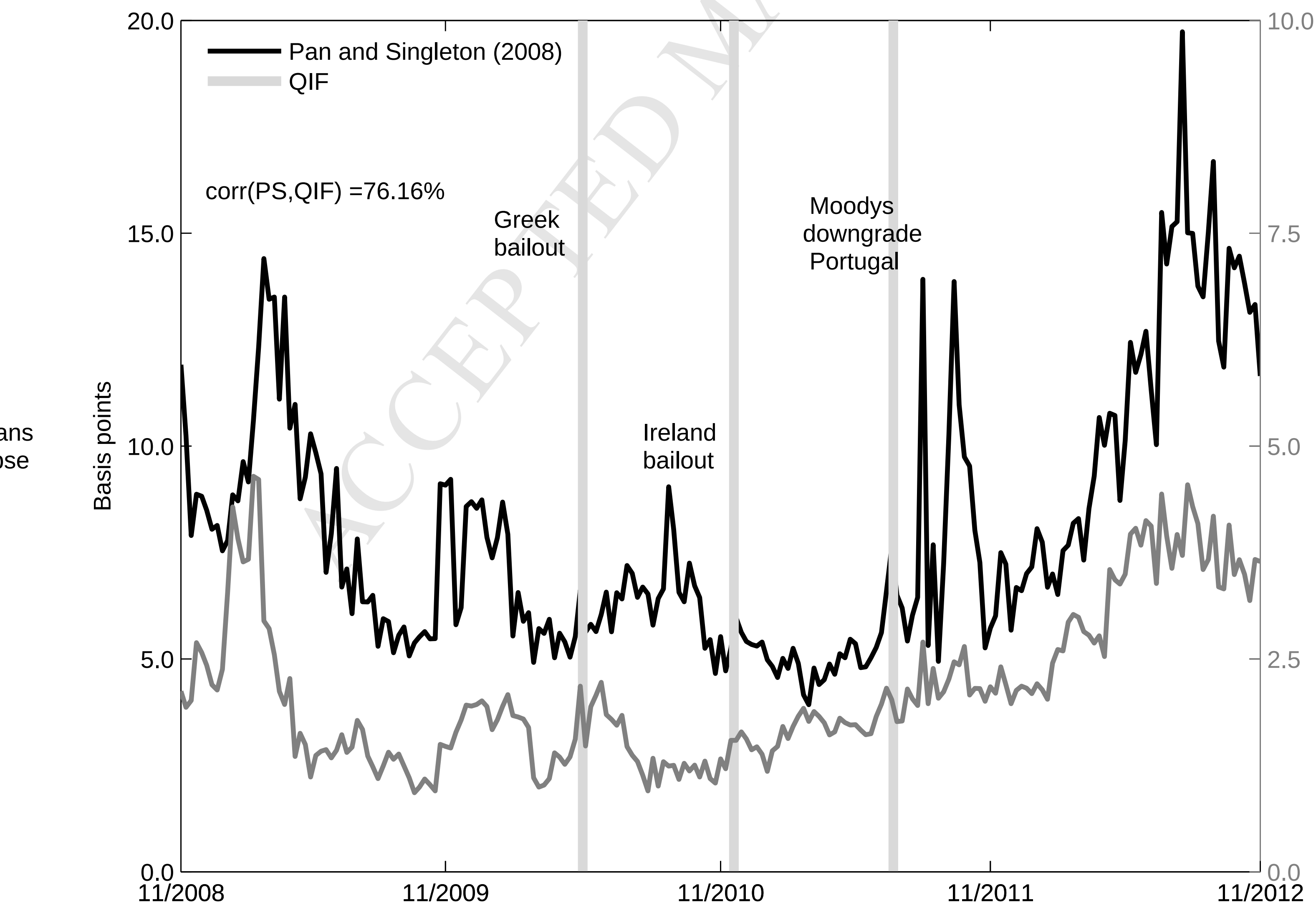
Figure 2: Cross-sectional median of sovereign CDS and qq-plots for different models

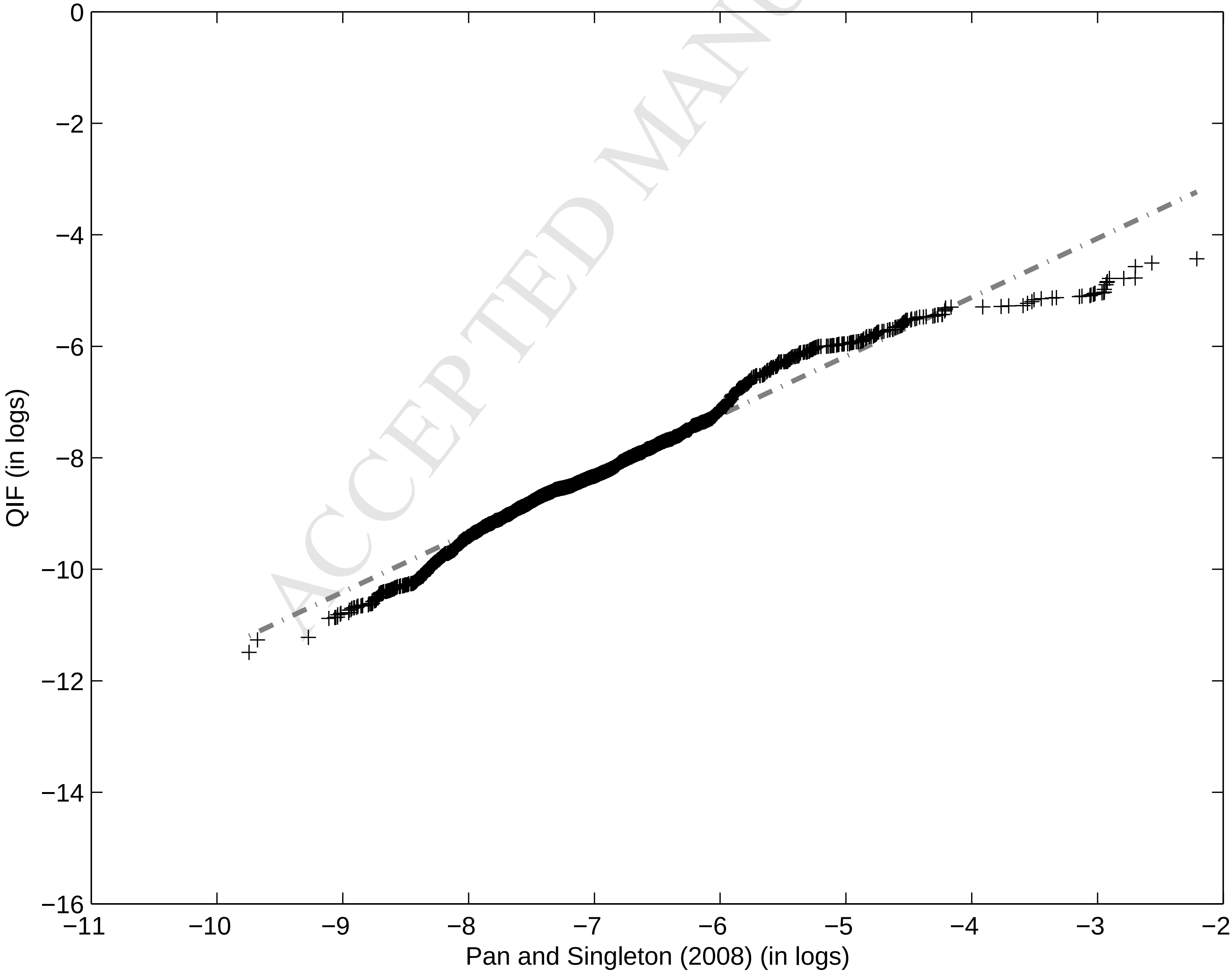


Cross-sectional medians (left column) and qq-plots (right column) of sovereign CDS spreads. Each row compares the different models. The first row shows the Pan and Singleton (2008) model against the quadratic intensity model (QIF). The second row contains the Pan and Singleton (2008) model against the Nelson and Siegel (1987) model. The third row depicts the QIF model against the Nelson and Siegel (1987) model.

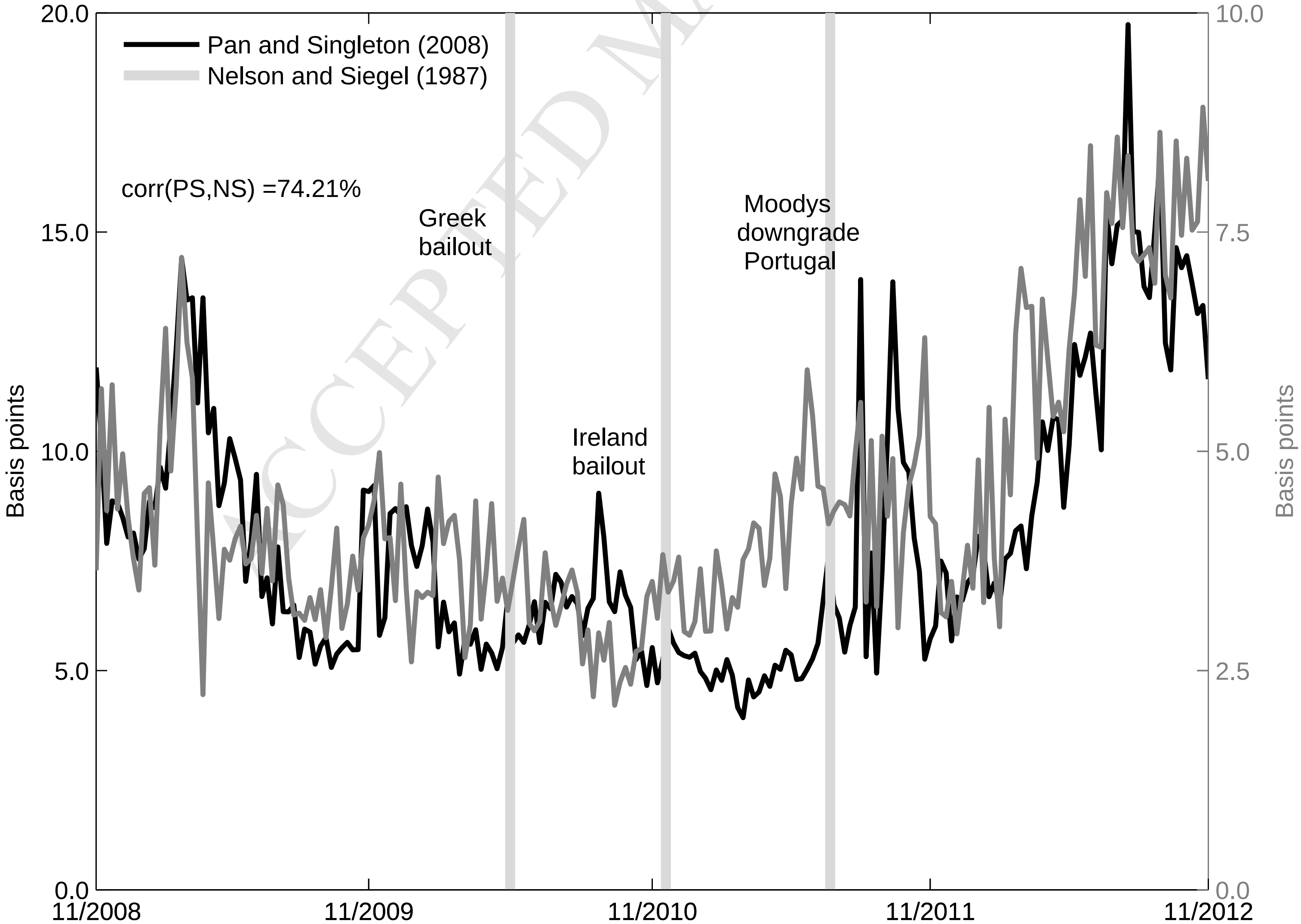

Median 1Y
Median 5Y
Median 10Y
Spread (bps)
500
450
400
350
300
250
200
150
100
50
0
01/2006
09/2007
06/2009
02/2011
11/2012
Bearn Stearns Collapse
Lehman Brothers Default
Greek bailout
Ireland bailout
Moodys downgrade Portugal

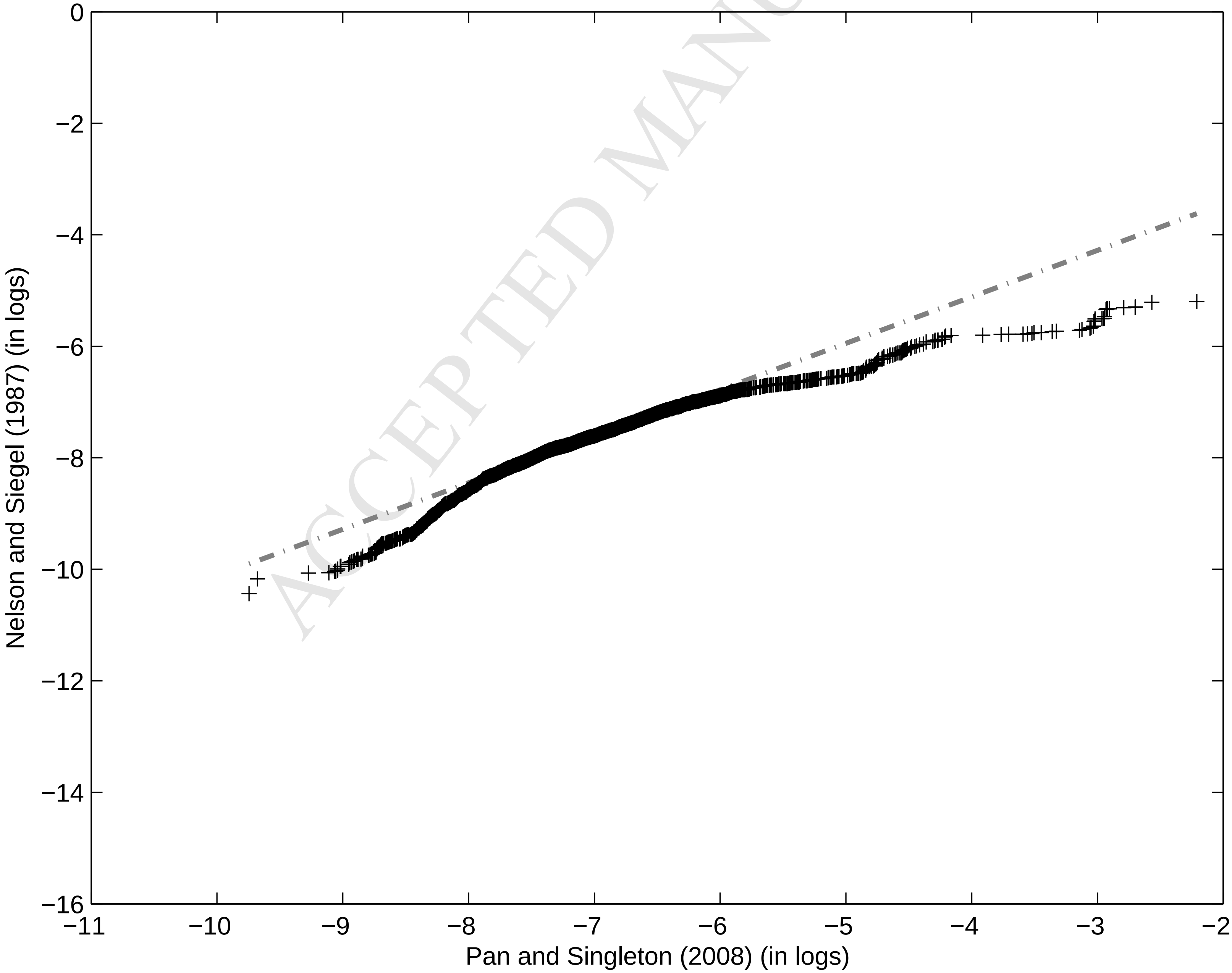

Q25
Q50
Q75
Spread (bps)
0
10
20
30
40
50
60
01/2006
09/2007
06/2009
02/2011
11/2012
Bearn Stearns
Collapse
Lehman
Brothers
Default
Greek
bailout
reland
bailout
Moodys
downgrade
Portugal


20.0
15.0
10.0
5.0
0.0
10.0
7.5
5.0
2.5
0.0
Basis points
Basis points
Pan and Singleton (2008)
QIF
corr(PS,QIF) =76.16%
Greek bailout
Ireland bailout
Moodys downgrade Portugal
11/2008
11/2009
11/2010
11/2011
11/2012
ans
ose

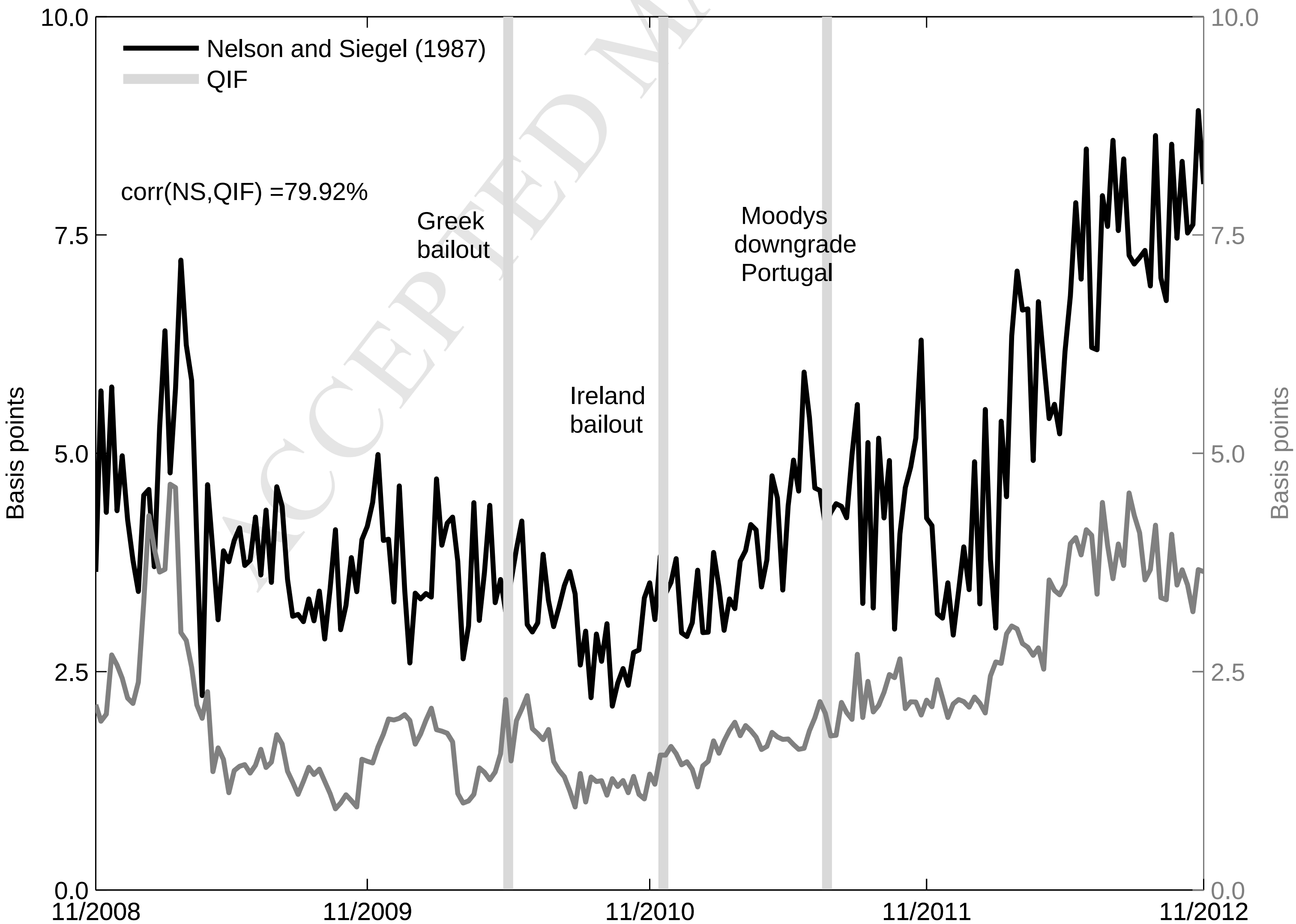

0
−2
−4
−6
−8
−10
−12
−14
−16
QIF (in logs)
−11
−10
−9
−8
−7
−6
−5
−4
−3
−2
Pan and Singleton (2008) (in logs)

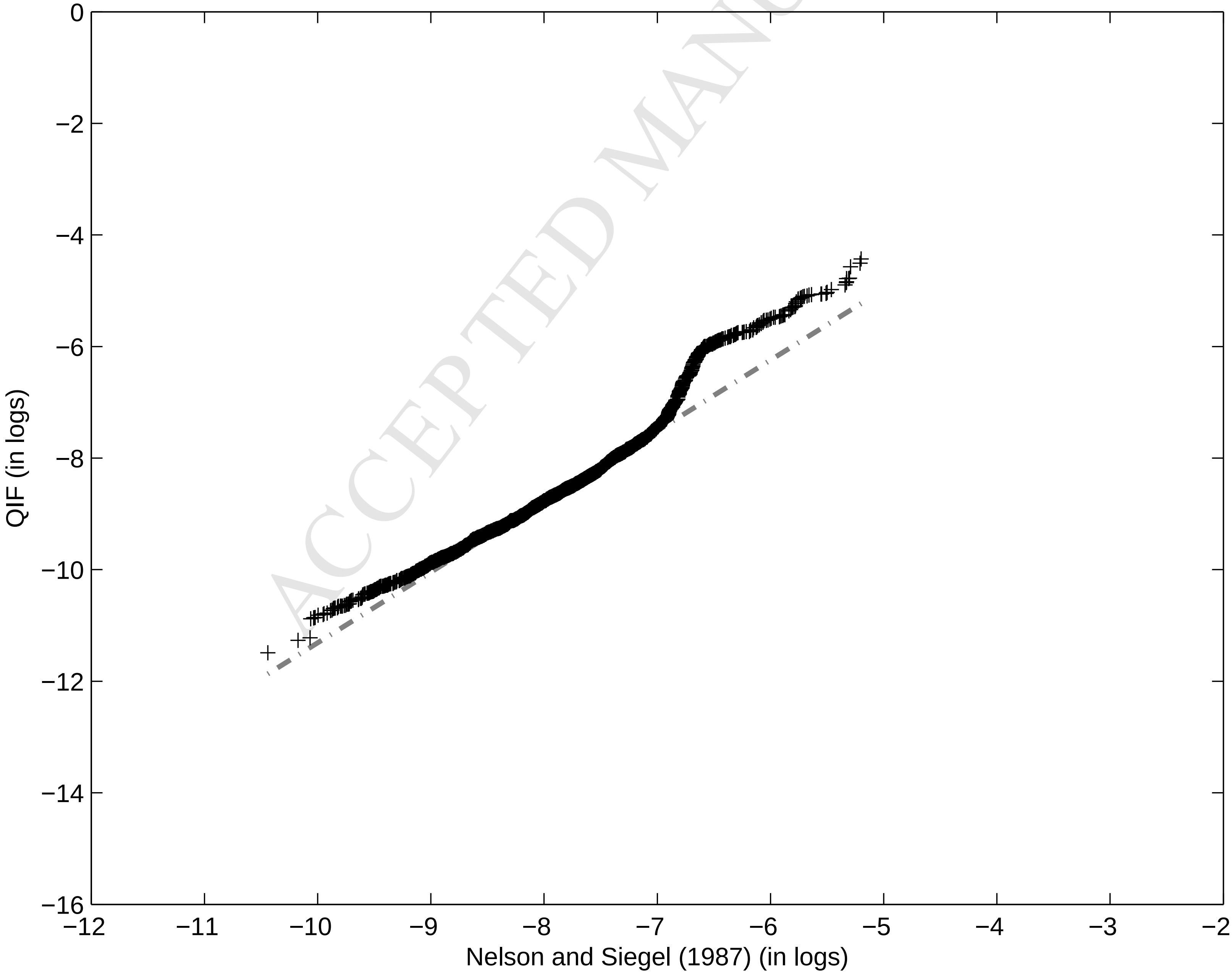
ans
ose

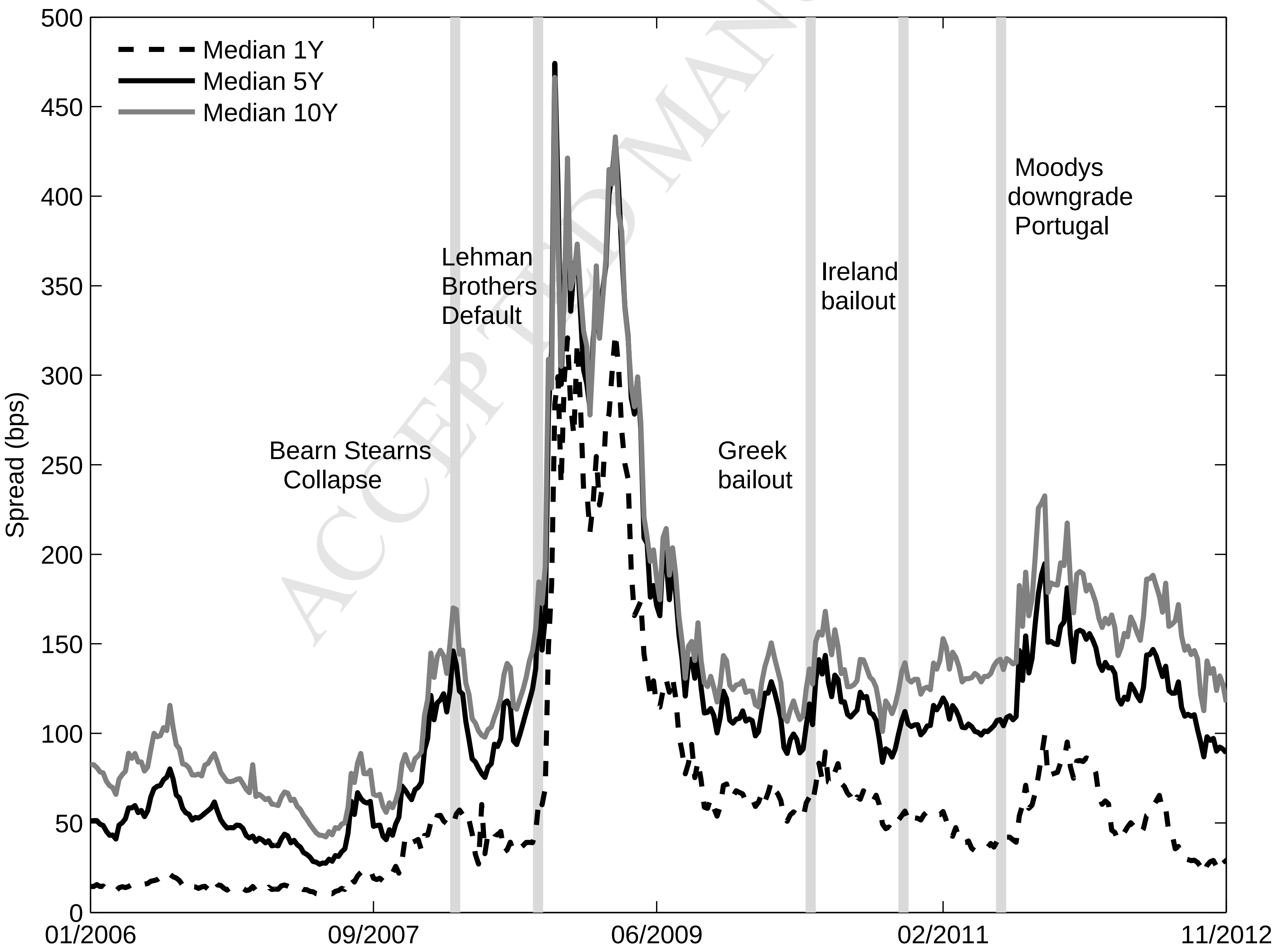

20.0
15.0
10.0
5.0
0.0
Basis points
10.0
7.5
5.0
2.5
0.0
Basis points
11/2008
11/2009
11/2010
11/2011
11/2012
Pan and Singleton (2008)
Nelson and Siegel (1987)
corr(PS,NS) =74.21%
Greek
bailout
Ireland
bailout
Moodys
downgrade
Portugal

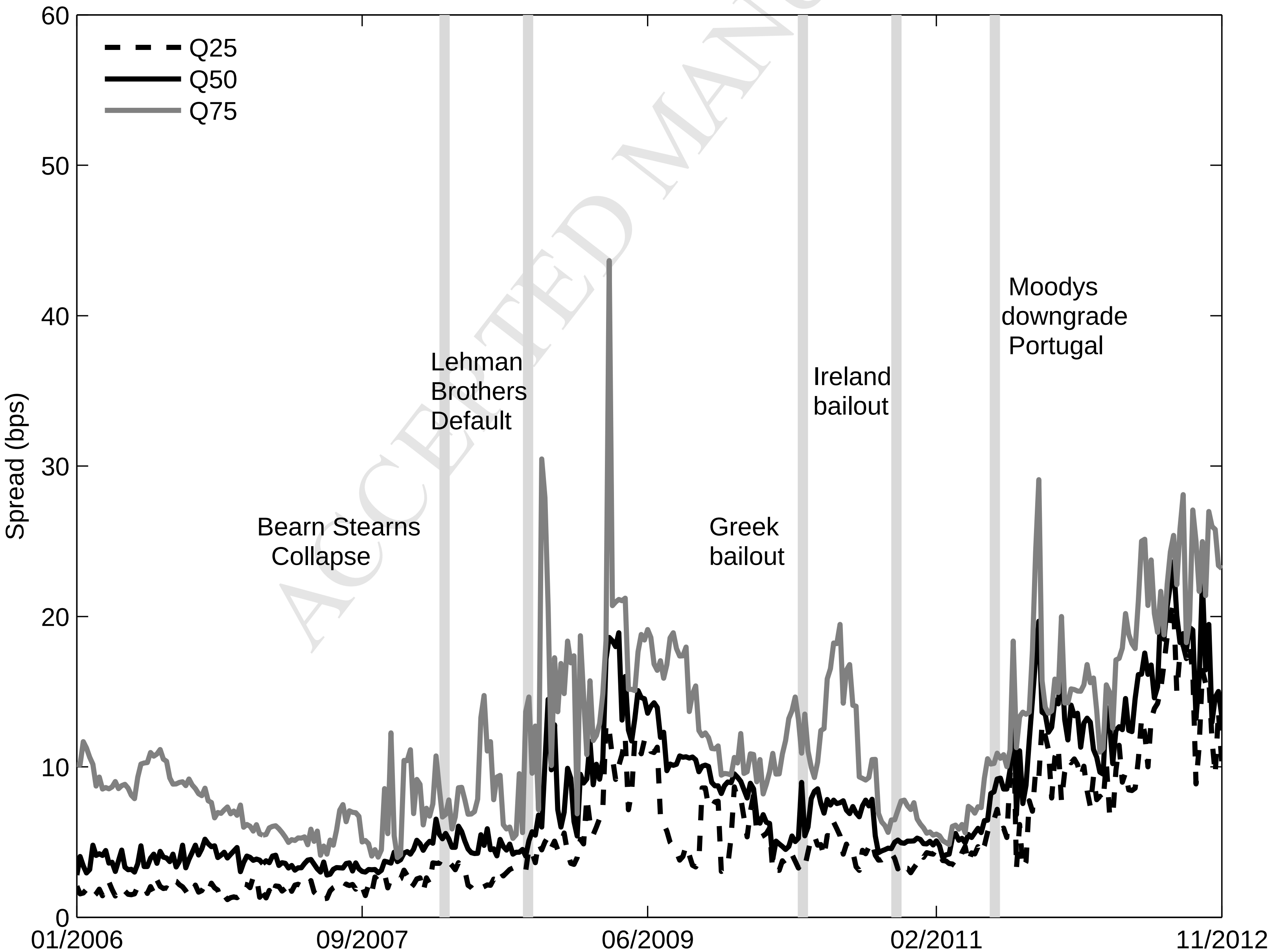

0
−2
−4
−6
−8
−10
−12
−14
−16
−11
−10
−9
−8
−7
−6
−5
−4
−3
−2
Nelson and Siegel (1987) (in logs)
Pan and Singleton (2008) (in logs)

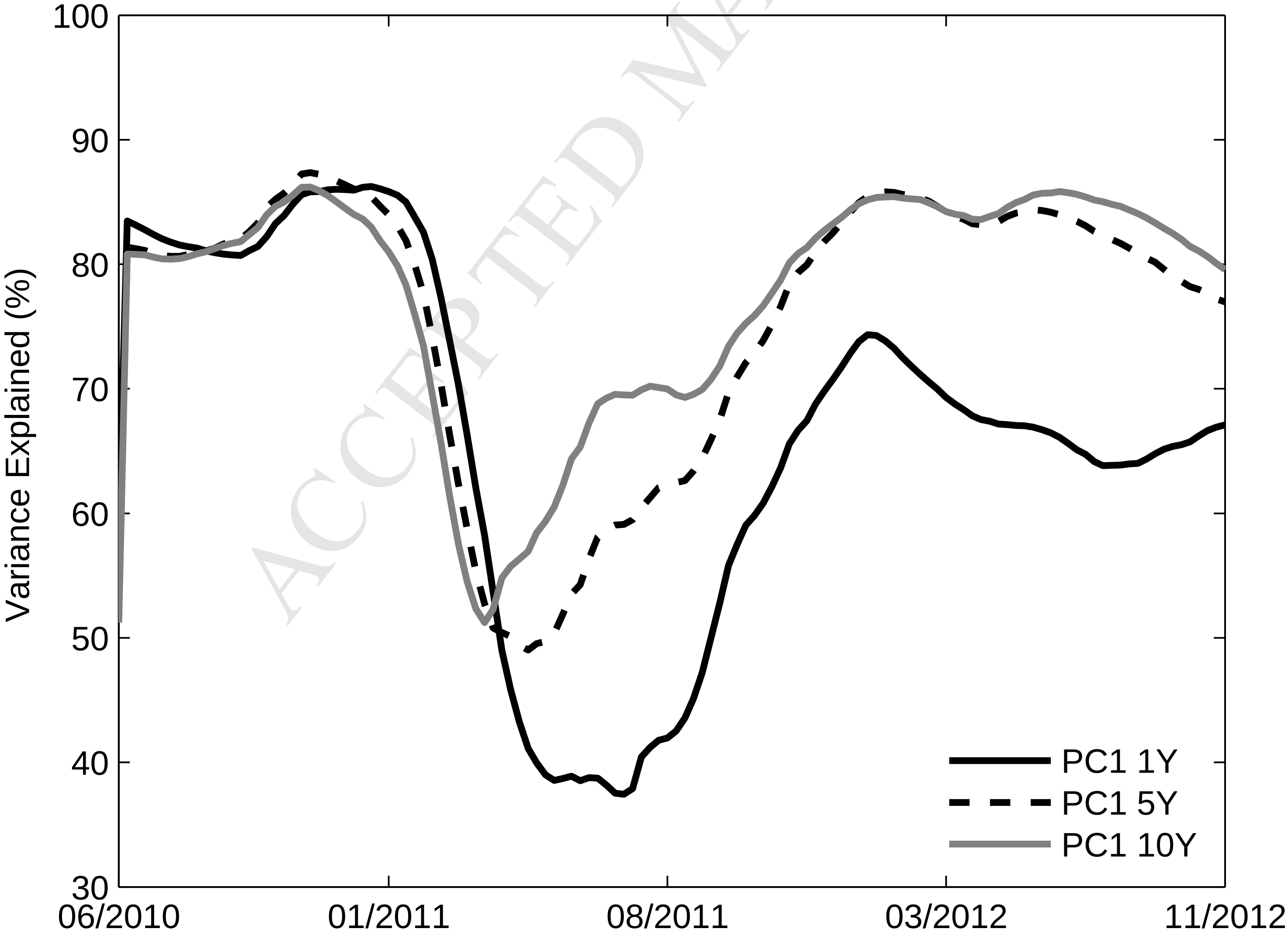
ans
ose


Nelson and Siegel (1987)
QIF
corr(NS,QIF) =79.92%
Greek
bailout
Ireland
bailout
Moodys
downgrade
Portugal
Basis points
Basis points
10.0
7.5
5.0
2.5
0.0
11/2008
11/2009
11/2010
11/2011
11/2012

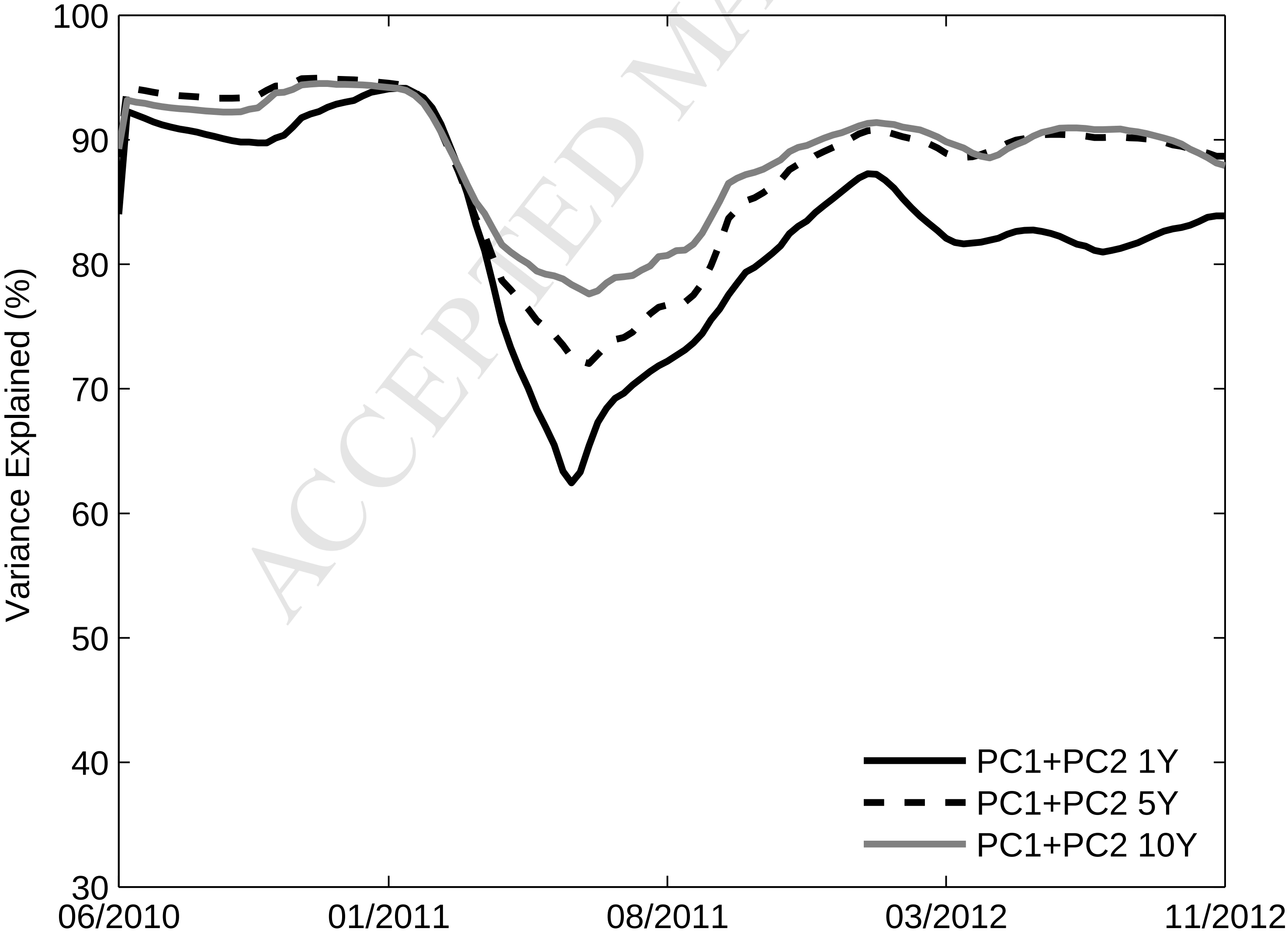

0
−2
−4
−6
−8
−10
−12
−14
−16
QIF (in logs)
−12
−11
−10
−9
−8
−7
−6
−5
−4
−3
−2
Nelson and Siegel (1987) (in logs)

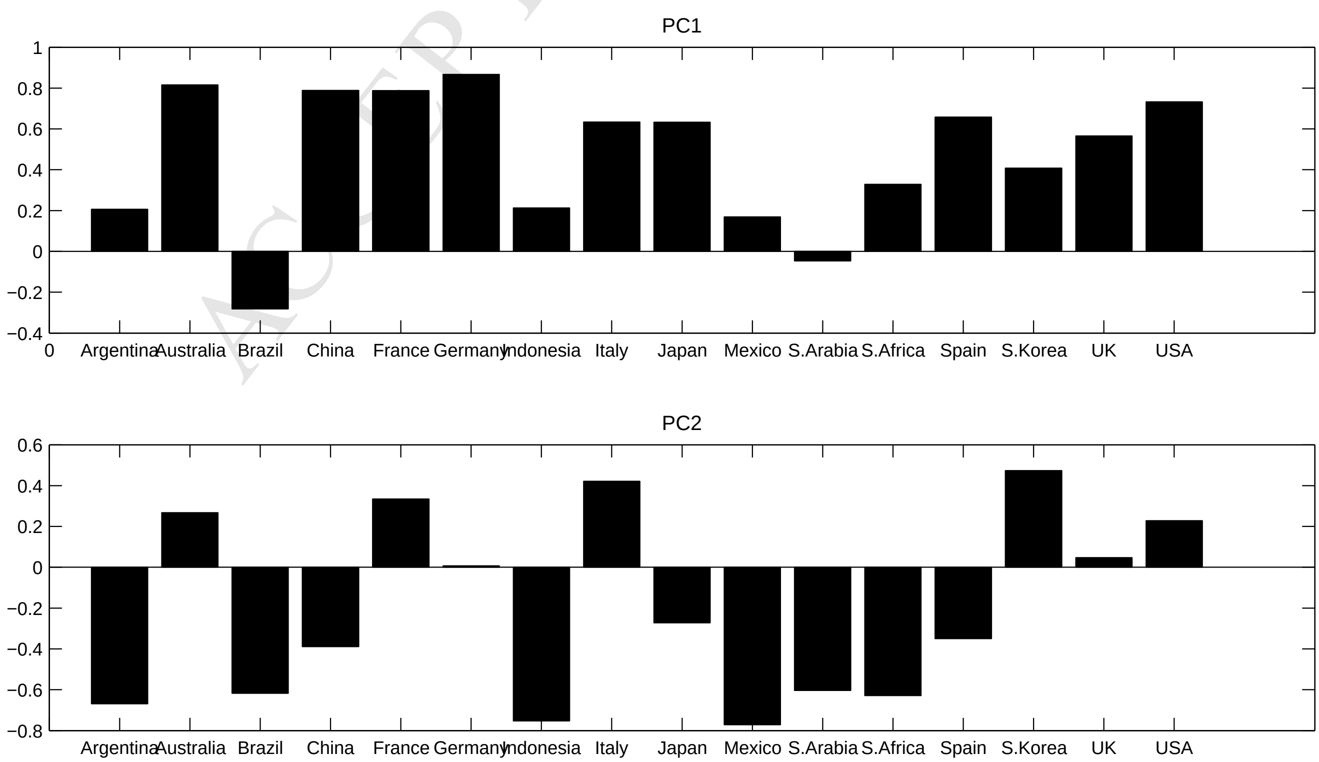

Median 1Y
Median 5Y
Median 10Y
Spread (bps)
500
450
400
350
300
250
200
150
100
50
0
01/2006
09/2007
06/2009
02/2011
11/2012
Bearn Stearns Collapse
Lehman Brothers Default
Greek bailout
Ireland bailout
Moodys downgrade Portugal


Q25
Q50
Q75
Spread (bps)
60
50
40
30
20
10
0
01/2006
09/2007
06/2009
02/2011
11/2012
Bearn Stearns Collapse
Lehman Brothers Default
Greek bailout
Ireland bailout
Moodys downgrade Portugal


100
90
80
70
60
50
40
30
Variance Explained (%)
06/2010
01/2011
08/2011
03/2012
11/2012
PC1 1Y
PC1 5Y
PC1 10Y

Figure(s)


100
90
80
70
60
50
40
30
Variance Explained (%)
06/2010
01/2011
08/2011
03/2012
11/2012
PC1+PC2 1Y
PC1+PC2 5Y
PC1+PC2 10Y


PC1
1
0.8
0.6
0.4
0.2
0
−0.2
−0.4
0
Argentina Australia Brazil China France Germany Indonesia Italy Japan Mexico S.Arabia S.Africa Spain S.Korea UK USA
PC2
0.6
0.4
0.2
0
−0.2
−0.4
−0.6
−0.8
Argentina Australia Brazil China France Germany Indonesia Italy Japan Mexico S.Arabia S.Africa Spain S.Korea UK USA

Appendix A. Data analysis

This Appendix contains a complete description of the CDS spread data and different variables related to their trading activity and liquidity.

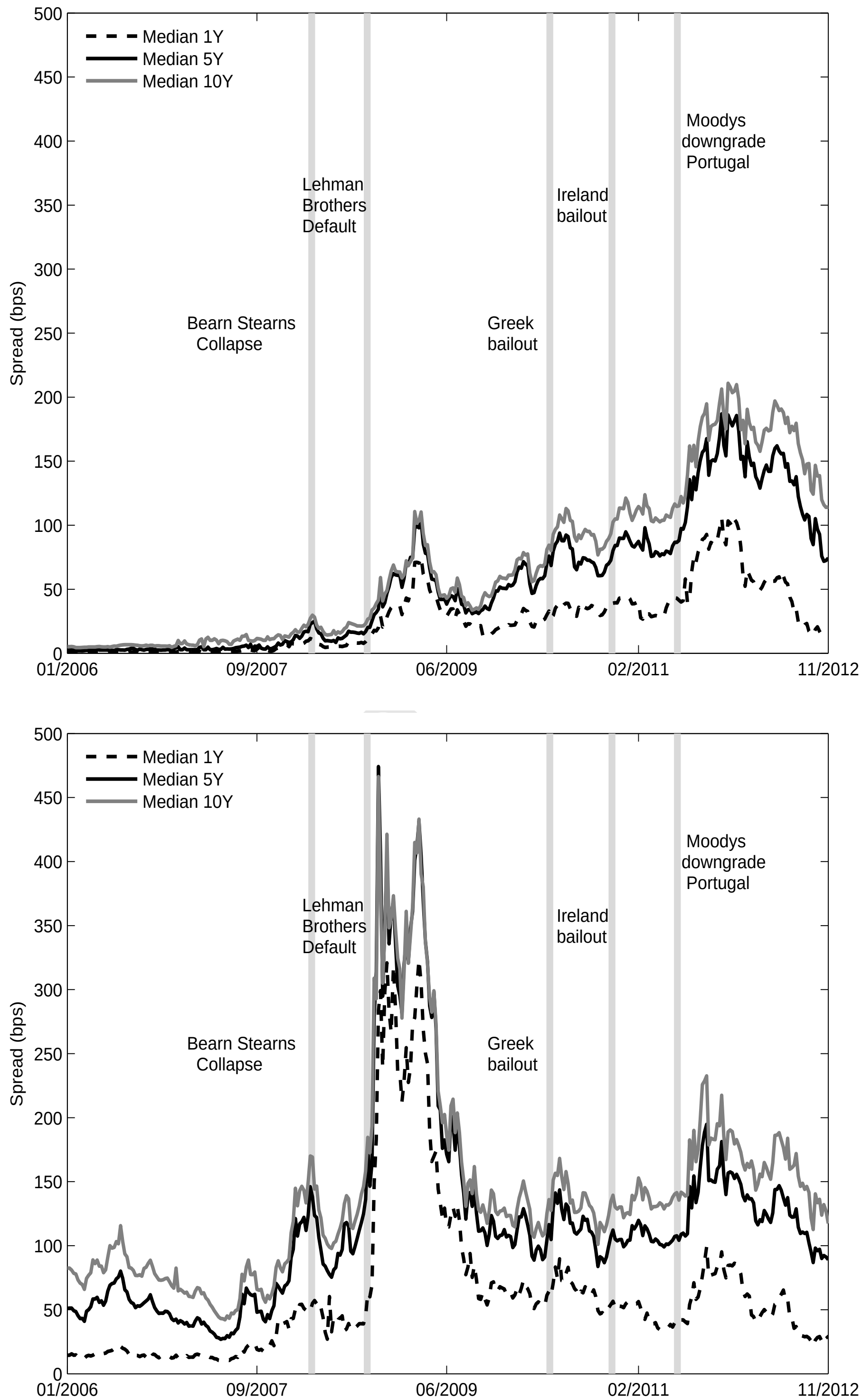
Appendix A.1. CDS spreads

Figure A.1 shows the time series dynamics of the cross-sectional medians of the sovereign CDS spreads at 1-, 5- and 10-year maturities over the total available sample, from January 1st, 2006 to November 9th, 2012. To account for likely structural differences across countries, we split the total sample into two subsamples. A first group is characterized by Advanced Economies (henceforth AE) and includes Australia, France, Germany, Italy, Japan, Spain, the UK, and the US. A second group is characterized by Emerging Economies (henceforth EE) and is formed by the remaining countries in the sample.

For both subsamples, the cross-sectional medians increase monotonically from 1- to 10-year maturities, thereby revealing an upward slope in the CDS spreads term-structure over the period. In addition, CDS spreads exhibit time-varying dynamics with considerable sensitivity to episodes of financial distress. More specifically, CDS spreads show similar responses to the largest systemic shocks over the period, peaking after the defaults of Bear Stearns (March 2008) and Lehman Brothers (September 2008). Although this pattern is clearly visible for both AE and EE groups, there are idiosyncratic patterns across countries that can be related to creditworthiness differences and that are worth discussing in detail. In particular, while the average CDS spreads in the AE group exhibit moderate values before the default of Bear Stearns at the different maturities, they increase steadily until mid 2011 as a consequence of the European debt crisis. These series exhibit a mean-reverting behavior in the final part of the sample, when the concerns in the Eurozone dissipated and default probabilities reverted to lower levels. On the other hand, while CDS spreads in the EE group largely increased around the collapse of Lehman Brothers, they show resilience against the idiosyncratic shocks that featured the European debt crisis. Lastly, CDS spreads in the AE group have a lower median and lower volatility than CDS spreads in EE group. The maximum cross-sectional median value rose to 450 basis points for emerging countries after Lehman Brother's collapse, while the peak in advanced economies was around 200 basis points in the midst of the European crisis.

Table A.1 reports the usual descriptive statistics (mean, median and standard deviation) of CDS spreads for each country in the sample. For the ease of exposition, we report these

Figure A.1: Cross-sectional median of sovereign CDS for different maturities



Cross-sectional medians of sovereign CDS spreads of different maturities for advanced (upper graph) and emerging (lower graph) economies. Advanced economies are Australia, France, Germany, Italy, Japan, Spain, the UK and the US. The maturities of CDS contracts are 1-, 5- and 10-year, respectively. Vertical bars denote some crisis events. The sample period spans from January 2006 to November 2012. Data frequency is weekly.

Table A.1: Descriptive statistics of sovereign CDS spreads

	1 Year			5 Year			10 Year			
Country	Mean	Median	Std.	Mean	Median	Std.	Mean	Median	Std.	Obs.
Argentina	855.99	417.60	1213.68	964.41	741.90	897.20	971.81	752.33	818.27	358
Australia	25.28	23.26	21.34	44.44	44.12	33.31	52.83	49.86	38.42	358
Brazil	66.68	54.89	58.44	145.45	125.15	68.66	183.24	159.82	65.94	358
China	36.40	28.02	34.56	75.08	70.66	52.20	91.33	85.87	56.96	358
France	28.43	18.64	34.56	58.68	36.59	63.73	67.95	40.01	72.10	358
Germany	13.70	10.12	14.09	33.20	30.34	30.68	41.87	32.98	38.59	358
Indonesia	115.81	69.65	135.04	220.09	174.77	146.64	267.99	227.39	134.62	358
Italy	105.96	51.38	136.00	148.06	99.36	157.39	152.20	103.43	149.60	358
Japan	18.74	13.78	18.48	51.68	49.84	40.56	67.74	61.69	53.23	358
Mexico	65.23	43.25	70.05	126.82	113.81	83.61	152.74	144.02	82.71	358
Saudi Arabia	80.46	78.08	33.46	115.66	105.33	52.18	126.61	116.90	54.03	228
South Africa	76.68	50.83	95.17	145.58	140.81	97.30	168.30	162.69	90.91	358
South Korea	72.14	45.62	90.36	107.71	97.71	91.43	122.58	115.01	89.50	358
Spain	115.71	61.41	130.30	154.04	93.08	163.13	153.47	94.36	154.73	358
UK	30.17	25.57	22.86	63.16	65.95	30.81	72.70	77.96	31.32	261
US	18.72	19.23	13.90	38.34	40.25	16.72	40.09	42.00	22.50	334

Summary of the main descriptive statistics of CDS spreads in levels for each country. Maturities are 1-, 5- and 10-year, respectively. Sample comprises from January 2006 to November 2012, with the exception of Saudi Arabia, the UK and the US, which covers from December 2007 to November 2012. Data frequency is weekly.

statistics for the representative cases of 1-, 5-, and 10-year maturities, noting that a complete analysis is available upon request. As expected from the previous discussion, there are significant differences in average spreads across maturities, consistent with the upward slope of the term structure discussed previously. Argentina is the economy with the lowest creditworthiness in the sample. Accordingly, the mean 5-year maturity CDS spread is 964.41, considerably greater than the spread of any other country in the sample. This series also exhibits a massive degree of volatility, given by a standard deviation of 897.20, which is caused by extreme observations in the upper tail recorded after the Lehman Brother's collapse. As discussed previously, there is a meaningful mean-volatility pattern in CDS spreads such that countries with higher spreads tend to consistently exhibit higher volatility levels as well. This result suggests that investors are more sensitive to news affecting default probabilities when creditworthiness is low. Not surprisingly Germany, widely seen as the safe haven by investors, is the economy with the overall best credit creditworthiness in the sample. The mean spread values for the 5-year German CDS contract is 33.20, with a standard deviation of 30.68, the smallest among the different countries analyzed.

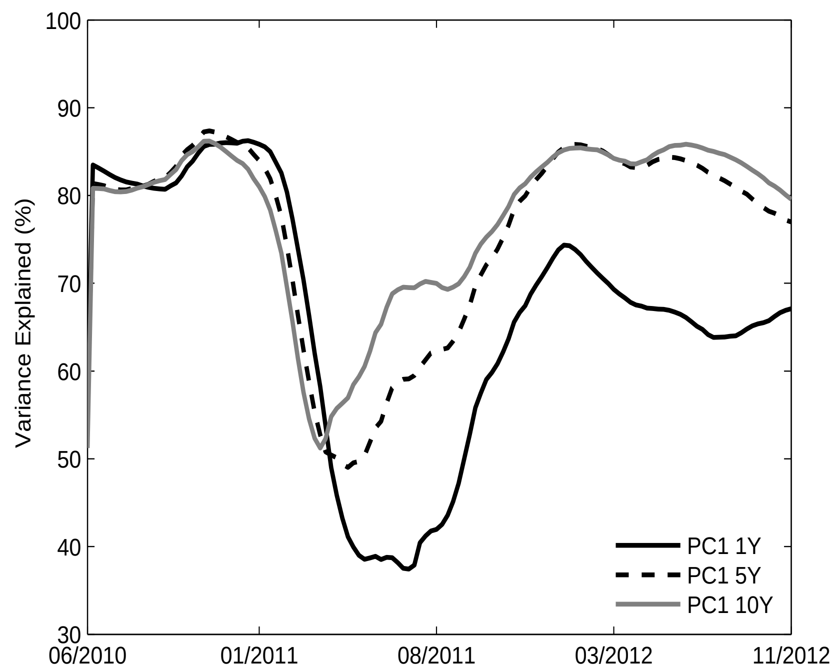
Previous literature on CDS have put forward the existence of a strong degree of commonality in sovereign CDS spreads. Principal Component Analysis (PCA) on the standardized CDS spread series confirms the existence of a strong commonality in the behavior of sovereign spreads. In particular, the first principal component (PC1) of the system explains approximately 74% of the total cross-country variation, which increases to nearly 88% when a second principal component (PC2) is included. Interestingly, the previous literature has not discussed whether the degree of commonality tends to be stable over time or exhibits time-varying patterns. Note that, for instance, a sharp reduction in the explanatory power of the first principal component will be indicative of idiosyncratic patterns that would likely lead to greater pricing errors. Because this question is particularly relevant in the context of this paper, we perform a dynamic PCA analysis, computing the principal components on the basis of the 100 most recent observations at any time in the sample on the basis of a rolling-window approach.

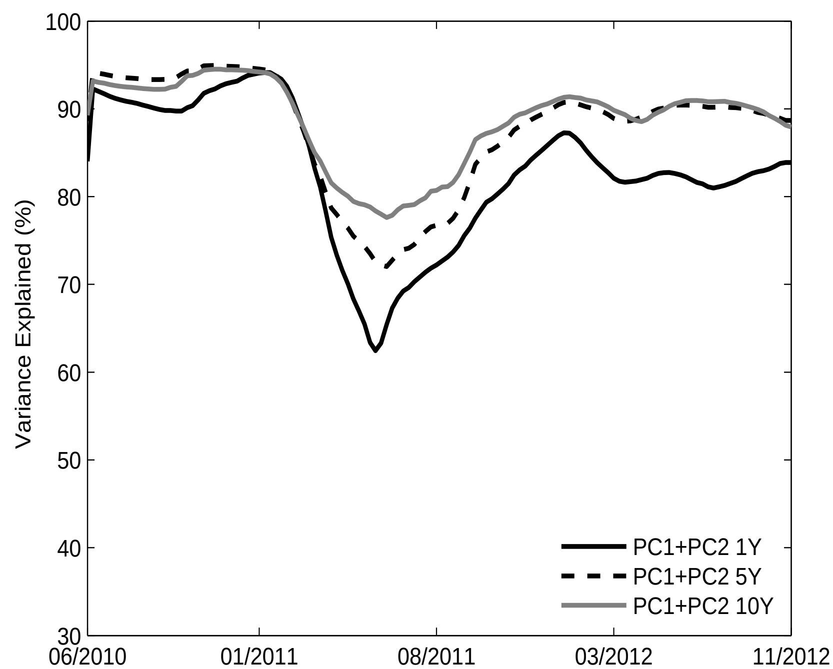
Figure A.2 shows the time series dynamics of the proportions of explained cross-country variability which are related to either the conditional PC1, or PC1 and PC2, given the 1-, 5- and 10-year maturities. Some interesting results emerge from this analysis. First, the share of variability explained by PC1 sharply declined from 90% to approximately 40% during the summer of 2011. This sheer decay affected all maturities and can be related to the European sovereign debt crisis. Adding a second factor reduces the magnitude of this decline, allowing the share total variability explained to reach about 65%, but still far from the average level achieved before this episode. Figure A.2 also shows that the proportion of explained variance over the total tends to be higher as the maturity increases, especially after August 2011. Finally, the levels of total variability explained by the first two principal components eventually reverted to the level observed before July 2011, with the exception of the 1-year maturity. Overall, this simple descriptive analysis suggests that a single factor (roughly corresponding with PC1) may not be able to consistently capture the full variation in the term structure of sovereign CDS spreads over time. Furthermore, there are important differences across the maturities that characterize the term structure, with the 1-year CDS contract exhibiting a more idiosyncratic behavior. As discussed in **?**, the most likely reason being that liquidity is lower at this maturity.

Appendix A.2. Trading activity and liquidity-related data

Together with CDS spreads, we observe different variables related to trading activity and liquidity. These variables are provided by the Depository Trust & Clearing Corporation (DTCC), which reports public information about real transactions of CDS contracts

Figure A.2: Evolution of principal components over time





Evolution of the aggregated explained variance of three first principal components using a rolling window scheme. Each window contains 100 observations.

since November 2008. In particular, we observe both the gross and net notional CDS positions, and the number of outstanding contracts in the CDS market. The gross notional value is the aggregate sum of the CDS contracts bought or sold for a single reference entity. The net notional values represents the aggregate net funds transference between protection sellers and buyers that could be required upon the occurrence of a credit event relating to a particular reference entity. Finally, the number of contracts reports the outstanding number of contracts for a given reference.

The sovereign CDS market has become one of the most active markets in the aftermath of the financial crisis. The relative volume of the sovereign CDS contracts traded is particularly sizeable. According to DTCC, the gross notational outstanding ranges from USD 0.71 trillions in November 14th, 2008 to USD 1.70 trillions in November 9th, 2012, showing the sharp increase in trading activity in CDS markets over recent years as a consequence of the financial crisis. Similarly, the net notional outstanding ranges from USD 0.08 trillions to USD 0.15 trillions over the same period. These series show a considerably degree of commonality across countries, reflecting the existence of common world-wide trends. For instance, the PC1 on either the gross or net notional outstanding series accounts for nearly 76% of the total variation of these series (a complete analysis is available upon request). Because the central premise in this paper is that mispricing in CDS markets can be related to illiquidity, Tables A.2 and A.3 report descriptive statistics on trading activity and liquidity based on these variables.

Table A.2 provides a summary of the weekly increments of the number of outstanding contracts, and the gross and net notional positions of the sovereign CDS written on the countries under study. For comparative purposes, we also include the relative position of the contracts with respect to the remaining G20 countries, i.e., the ratio of each country over the total G-20 group. The sample available spans the period November 14th, 2008 to November 9th, 2012. Note that, since trade-related information is not available for Saudi Arabia, this country has been excluded from the analysis. The weekly average increment in the number of contracts over the sample period is of approximately 20 contracts, with the mean gross and net position sizes reaching USD 318.23 and 20.63 millions, respectively. Trading activity is far from being homogeneous across the different countries in the period analyzed. In particular, Italy and Spain show the highest increments in the number of contracts and gross outstanding volumes, reflecting the financial tensions of these countries during the European debt crisis. Similarly, the overall net position on CDS has largely

Table A.2: Trading activity statistics

	Absolute measures (in differences)						Relative measures (in levels)						
	Contracts		Gross vol. (USD mill.)		Net vol. (USD mill.)		Contracts (%)		Gross vol. (%)		Net vol. (%)		
Country	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Obs.
Argentina	-8.10	139.49	-65.41	1131.25	-4.67	88.93	7.68	2.05	4.59	1.10	1.72	0.48	208
Australia	19.52	57.22	199.93	490.71	22.82	91.42	1.85	1.16	1.21	0.70	1.99	1.17	185
Brazil	-8.47	332.03	41.30	3331.37	27.03	287.98	15.80	3.90	13.56	2.16	11.55	0.61	208
China	30.75	143.53	267.06	1132.89	35.12	146.53	5.66	1.34	3.45	0.58	3.84	1.43	208
France	33.45	219.88	739.41	3401.11	58.43	388.13	4.57	2.19	6.74	2.02	11.27	2.54	208
Germany	24.66	114.78	548.28	2375.90	34.98	277.43	3.48	1.04	7.05	0.80	12.05	0.77	208
Indonesia	6.30	142.31	49.67	1056.35	6.57	76.64	6.52	1.25	3.22	0.64	1.98	0.26	208
Italy	45.14	309.60	1123.34	6169.96	16.49	473.74	9.59	1.14	22.28	1.14	18.95	4.54	208
Japan	35.61	173.52	345.55	1593.84	46.36	118.10	4.61	2.52	3.14	1.33	4.46	1.66	208
Mexico	10.54	185.17	212.91	1656.96	23.71	145.28	12.77	2.76	9.65	1.22	5.87	0.55	208
South Africa	10.96	92.52	98.21	670.39	1.58	78.67	6.37	1.19	3.60	0.53	1.87	0.44	208
South Korea	21.05	238.28	152.41	2063.22	6.86	149.90	9.43	1.58	5.53	1.20	3.68	0.93	208
Spain	38.53	320.06	697.09	5201.09	-8.15	334.01	7.03	1.61	10.76	0.95	12.03	2.24	208
UK	20.42	100.69	280.22	1357.33	31.60	194.12	3.95	1.57	3.96	0.98	6.48	1.92	208
US	4.09	39.39	83.46	640.63	10.74	127.24	0.90	0.40	1.39	0.37	2.49	0.52	208

Summary of the main descriptive statistics of CDS volumes in increments for each country. Relative measure includes the ratio of each country value with respect to the remaining G20 countries. Sample comprises from November 2008 to November 2012. Data frequency is weekly.

increased for other advanced economies in the EMU area, particularly, France, suggesting effects related to financial contagion. The average of net notional CDS positions over the period is negative for Argentina and Spain, and tends to exhibit larger positive values for the economies with better creditworthiness in the sample. Negative values of this variable can be related to offsetting transactions in the CDS market. In this way, the net volume can be taken as a crude proxy for professional arbitrage activity and will play a major role in the analysis of determinants in Section 4 of the article.

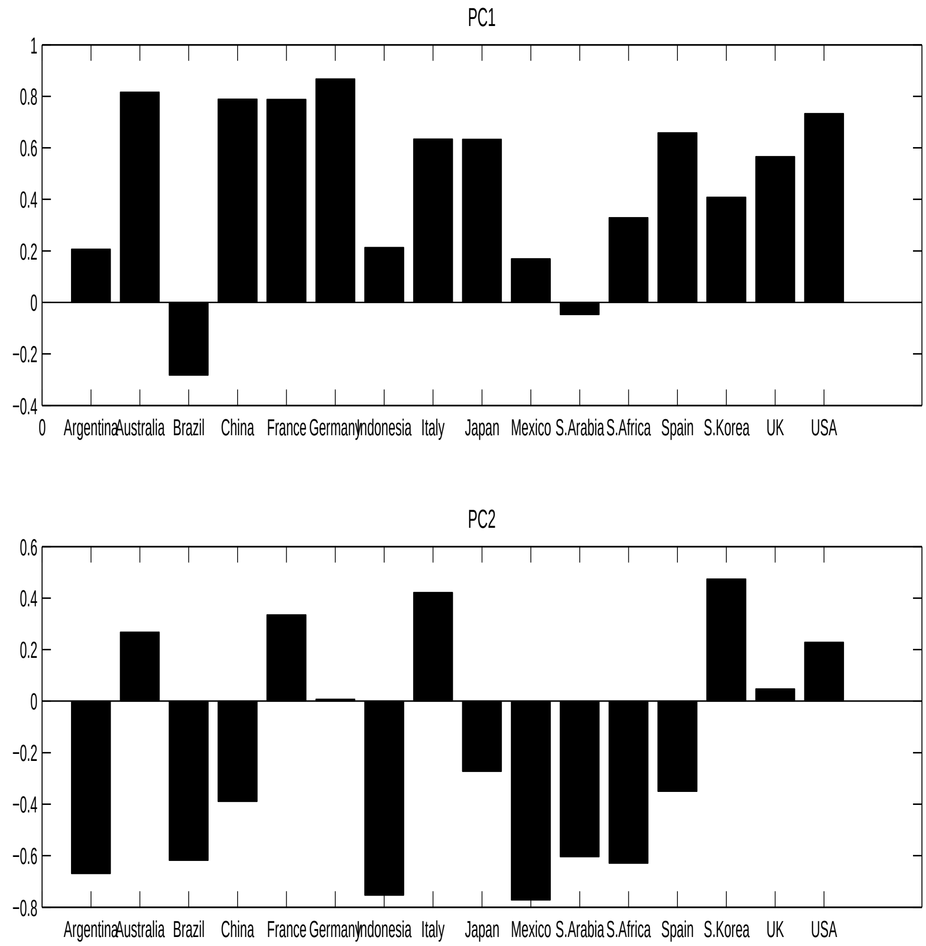
Table A.3 reports descriptive statistics (mean, median, and standard deviation) for the bid-ask spreads of CDS contracts for each country. For conciseness, we report these descriptives at 1-, 5- and 10-year maturities, noting that a complete study on all maturities is available upon request. In addition, Table A.3 reports descriptive statistics for the so-called veracity index, an indicator of data reliability at each maturity elaborated directly by the data provider. The analysis on bid-ask spreads essentially reveals the same features discussed previously. Clearly, there exists a negative relationship between bid-ask spread and creditworthiness. Countries with lower default probabilities exhibit smaller bid-ask spreads uniformly over the maturities. Similarly, and consistent with the previous discussion, the CDS with higher average bid-ask spreads are also the more volatile, showing a greater disagreement on fundamental values. In particular, while Germany and France are the countries with the lowest bid-ask averages and standard deviations, Argentina and Saudi Arabia in the EE group exhibit the highest values of these statistics in the sample. Interestingly, the average bid-ask spreads are higher at the 1-year maturity, suggesting that sovereign CDS investors seem to incorporate their liquidity concerns about a country in the short-term maturities of the curve, as pointed out by Pan and Singleton (2008). Finally, the analysis on the veracity index reveals similar values with no particular pattern across countries, indicating that the CDS sample is representative of the real trade quotes finally traded in the market.

Table A.3: Liquidity and veracity index of CDS spreads

	Bid-ask spread									Veracity index			
	1-Year			5-Year			10-Year			All maturities			
Country	Mean	Median	Std.	Mean	Median	Std.	Mean	Median	Std.	Mean	Median	Std.	Obs.
Argentina	79.03	28.82	139.30	36.75	12.48	83.41	39.37	15.00	86.89	1.71	1.80	0.22	358
Australia	6.63	5.63	5.39	4.81	3.39	3.59	5.03	3.96	3.16	1.91	1.90	0.03	358
Brazil	7.01	5.01	5.75	3.54	2.58	2.93	5.03	4.00	2.73	1.71	1.80	0.21	358
China	6.94	5.20	6.77	4.64	3.90	3.91	5.00	4.24	2.88	1.84	1.90	0.14	358
France	3.49	3.06	2.86	3.11	2.92	1.74	4.50	3.29	2.70	1.83	1.80	0.09	358
Germany	2.60	2.00	2.38	2.65	2.62	1.32	3.55	3.12	2.16	1.85	1.80	0.09	358
Indonesia	18.11	10.54	20.55	9.07	5.18	10.40	10.64	8.06	9.69	1.78	1.90	0.21	358
Italy	9.44	6.70	9.36	4.52	3.70	3.31	6.72	4.41	4.66	1.80	1.80	0.12	358
Japan	3.88	2.00	4.66	3.88	3.00	2.40	4.47	3.58	2.63	1.92	1.90	0.07	358
Mexico	7.28	5.67	5.64	3.77	3.00	2.59	4.96	4.00	2.53	1.77	1.80	0.17	358
Saudi Arabia	24.83	16.65	21.05	15.58	10.01	13.58	13.52	9.36	10.31	1.92	1.90	0.04	228
South Africa	13.68	7.01	17.75	6.45	4.32	7.55	8.03	5.19	7.03	1.77	1.80	0.17	358
South Korea	10.01	6.23	12.09	5.09	4.00	4.51	5.31	4.29	3.50	1.77	1.80	0.17	358
Spain	9.56	7.41	10.03	4.87	3.71	3.04	6.31	4.48	5.37	2.05	1.80	0.49	358
UK	4.98	3.82	4.14	4.20	3.73	2.12	5.03	4.13	2.69	1.82	1.80	0.06	261
US	6.20	5.90	3.21	5.15	4.94	2.08	5.56	4.90	2.53	1.85	1.80	0.06	334

Descriptive statistics of bid-ask spreads and veracity index for available G20 countries. Maturities for bid-ask spreads are 1-, 5- and 10-year, respectively. Veracity index is computed across all available maturities. Sample comprises from January 2006 to November 2012, with the exception of Saudi Arabia, the UK and the US, which covers from December 2007 to November 2012. Data frequency is weekly.

Appendix B. Loading coefficients for principal components of the noise measure



Appendix C. Panel-data estimates of noise determinants to alternative classifications of creditworthiness

In order to gain further insight on the role played by the creditworthiness, we have gathered the sovereign CDS sample according to the investment- and speculative-grade status of the bonds to explore the role played by the creditworthiness in our results. We have considered two subsamples formed by AAA to A and BBB to B rated sovereigns. The first group is formed by Australia, China, France, Germany, Japan, Saudi Arabia, South Korea, UK and US, the second by the remaining countries. These results are provided in Tables C.4 and C.5.

Table C.4: Panel-data estimates of noise determinants for AAA to A rated sovereigns

	Two-way cluster			**Pane data Fixed Effects**			**Instrumental Fixed Effects**			**Predictive Two-way cluster**		
	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value
						Panel A.- Model I						
logBidaskspread5Y	0.3335	0.1547	0.03	0.3335	0.1536	0.07	0.3343	0.0593	0.00	0.3148	0.1542	0.04
logContracts	0.5043	0.2514	0.05	0.5043	0.2463	0.08	0.5071	0.0597	0.00	0.4866	0.2518	0.05
logNetvolume	-0.2189	0.2033	0.28	-0.2189	0.2007	0.31	-0.2226	0.0758	0.00	-0.1906	0.2038	0.35
Marketvolatility	0.3012	0.6620	0.65	0.3012	0.6215	0.64	0.4287	0.7141	0.55	0.2743	0.3886	0.48
Default	0.3107	0.1442	0.03	0.3107	0.1390	0.06	0.3217	0.0418	0.00	0.3285	0.1447	0.02
Constant	-7.0599	3.1561	0.03	-6.7702	2.9969	0.06	-6.7268	1.3025	0.00	0.4559	2.9425	0.88
Country Dummies	Yes	Yes	Yes	No	No	No	No	No	No	Yes	Yes	Yes
Observations	1519	1519	1519	1519	1519	1519	1505	1505	1505	1505	1505	1505
R2-coefficient	0.9264	0.9264	0.9264	0.9264	0.9264	0.9264	-	-	-	0.9259	0.9259	0.9259
	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value
						Panel B.-Model II						
logBidaskspread5Y	0.4266	0.1352	0.00	0.4266	0.1328	0.02	0.4362	0.0375	0.00	0.4110	0.1274	0.00
ΔlogContracts	-0.0557	0.5188	0.92	-0.0557	0.4916	0.91	-0.0440	0.4283	0.92	0.0076	0.4895	0.99
ΔlogNetvolume	-1.5748	0.6889	0.02	-1.5748	0.6259	0.04	-1.6643	0.4640	0.00	-1.9384	0.5946	0.00
ΔMarketvolatility	0.2521	0.4206	0.55	0.2521	0.2747	0.39	0.2269	0.5855	0.70	0.1090	0.4263	0.80
ΔDefault	0.0972	0.6523	0.88	0.0972	0.5788	0.87	0.2039	0.2777	0.46	-0.1055	0.6626	0.87
Constant	-7.9164	0.1516	0.00	-7.5782	0.1876	0.00	-7.5911	0.0546	0.00	-7.9019	0.1428	0.00
Country Dummies	Yes	Yes	Yes	No	No	No	No	No	No	Yes	Yes	Yes
Observations	1511	1511	1511	1511	1511	1511	1503	1503	1503	1503	1503	1503
R2-coefficient	0.9134	0.9134	0.9134	0.9134	0.9134	0.9134	-	-	-	0.9127	0.9127	0.9127

Panel data estimates for noise measure using different standard estimation methods for high quality countries (Australia, China, France, Germany, Japan, Saudi Arabia, South Korea, UK and US). The mispricing errors have been computed using the Pan and Singleton (2008) model. Panel A shows the results for variables in levels and Panel B for variables in differences. First column corresponds with pooled time-series cross-sectional regressions with two-way cluster-robust standard errors accounting for country and week clusters. Second column shows the fixed effect with robust standard errors to autocorrelation and heteroskedasticity. The last two columns present the estimation for fixed effects and two-cluster using lagged regressors.

Table C.5: Panel-data estimates of noise determinants for BBB to B rated sovereigns

	Two-way cluster			**Pane data Fixed Effects**			**Instrumental Fixed Effects**			**Predictive Two-way cluster**		
	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value
Panel A.- Model I												
logBidaskspread5Y	0.5742	0.0741	0.00	0.5742	0.0693	0.00	0.5829	0.0405	0.00	0.5537	0.0866	0.00
logContracts	0.8745	0.1357	0.00	0.8745	0.1268	0.00	0.8394	0.0733	0.00	0.8744	0.1388	0.00
logNetvolume	-0.3095	0.1292	0.02	-0.3095	0.1256	0.04	-0.2724	0.0804	0.00	-0.2530	0.1098	0.02
Marketvolatility	1.1088	0.5782	0.06	1.1088	0.5076	0.07	1.0517	0.6173	0.09	0.0795	0.3152	0.80
Default	0.0601	0.0823	0.47	0.0601	0.0769	0.46	0.0734	0.0414	0.08	0.1021	0.0916	0.27
Constant	-8.1625	3.6345	0.03	-7.6916	3.3460	0.06	-8.2513	1.7451	0.00	-9.4761	2.8230	0.00
Country Dummies	Yes	Yes	Yes	No	No	No	No	No	No	Yes	Yes	Yes
Observations	1612	1612	1612	1612	1612	1612	1596	1596	1596	1596	1596	1596
R2-coefficient	0.9480	0.9480	0.9480	0.9480	0.9480	0.9480	-	-	-	0.9475	0.9475	0.9475

	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value	Estimate	Est. Error	p-value
Panel B.-Model II												
logBidaskspread5Y	0.6385	0.0495	0.00	0.6385	0.0479	0.00	0.6489	0.0252	0.00	0.6271	0.0537	0.00
ΔlogContracts	-0.2237	0.5515	0.69	-0.2237	0.4882	0.66	-0.2580	0.4488	0.57	-0.1759	0.5174	0.73
ΔlogNetvolume	0.0547	0.5434	0.92	0.0547	0.5541	0.92	0.0388	0.5127	0.94	0.0922	0.4380	0.83
ΔMarketvolatility	0.3099	0.4566	0.50	0.3099	0.4187	0.48	0.2071	0.4863	0.67	0.0819	0.2903	0.78
ΔDefault	-0.5225	0.5701	0.36	-0.5225	0.5513	0.38	-0.3010	0.2724	0.27	-0.3332	0.5795	0.57
Constant	-6.9585	0.1648	0.00	-7.0214	0.0887	0.00	-7.0354	0.0470	0.00	-7.9613	0.1918	0.00
Country Dummies	Yes	Yes	Yes	No	No	No	No	No	No	Yes	Yes	Yes
Observations	1604	1604	1604	1604	1604	1604	1594	1594	1594	1594	1594	1594
R2-coefficient	0.9426	0.9426	0.9426	0.9426	0.9426	0.9426	-	-	-	0.942	0.942	0.942

Panel data estimates for noise measure using different standard estimation methods for low quality countries (Argentina, Brazil, Indonesia, Italy, Mexico, South Africa and Spain). The mispricing errors have been computed using the Pan and Singleton (2008) model. Panel A shows the results for variables in levels and Panel B for variables in differences. First column corresponds with pooled time-series cross-sectional regressions with two-way cluster-robust standard errors accounting for country and week clusters. Second column shows the fixed effect with robust standard errors to autocorrelation and heteroskedasticity. The last two columns present the estimation for fixed effects and two-cluster using lagged regressors.